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THESIS

US ARMY'S DELAYED ENTRY PROGRAM:
ATTRITION MODELING

by

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September, 1991

Thesis Advisor:

Donald R. Barr

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<p>The United States Recruiting Command (USAREC) utilizes the Delayed Entry Program (DEP) as the foundation for their management of the continuous flow of recruits into the training base. Though there are many benefits of the DEP, a major shortcoming is that some DEP members do not enlist, becoming DEP losses. This is costly in terms of valuable resources such as lost recruiter time, and the potential for training seats being unfilled. Any effort which assists in reducing DEP loss would be a valuable contribution. This research models individual level DEP loss using multivariate dichotomous logistic regression. Explanatory variables used were individual, demographic, and USAREC policy in nature. Modeling efforts used data that were easily accessible to USAREC to ensure ease of potential future use. Univariate analysis was conducted on candidate explanatory variables prior to model building. The model was built using forward and backward stepwise logistic regression. Final model refinement included scaling of interval variables and the addition of one interaction term. Using statistical tests, the model as a whole was determined to exhibit some lack of fit. Closer analysis indicated that the model does perform well across many levels of estimated probability of DEP loss. Using USAREC's red, amber, green DEP loss risk classification system, the model appears to have significant predictive powers. The model also performed well using this classification system for a validation data set. It is concluded that this fitted model could prove useful in supplementing the field experience of the recruiter in predicting DEP loss risk of individual recruits.</p>				
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Attrition Modeling

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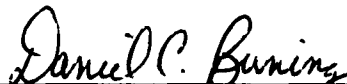
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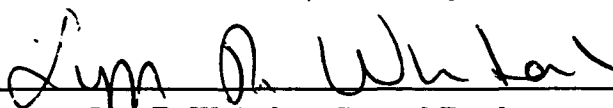


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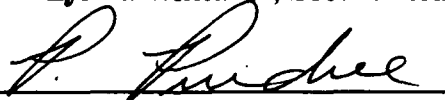
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ABSTRACT

The United States Recruiting Command (USAREC) utilizes the Delayed Entry Program (DEP) as the foundation for their management of the continuous flow of recruits into the training base. Though there are many benefits of the DEP, a major shortcoming is that some DEP members do not enlist, becoming DEP losses. This is costly in terms of valuable resources such as lost recruiter time, and the potential for training seats being unfilled. Any effort which assists in reducing DEP loss would be a valuable contribution.

This research models individual level DEP loss using multivariate dichotomous logistic regression. Explanatory variables used were individual, demographic, and USAREC policy in nature. Modeling efforts used data that were easily accessible to USAREC to ensure ease of potential future use. Univariate analysis was conducted on candidate explanatory variables prior to model building. The model was built using forward and backward stepwise logistic regression. Final model refinement included scaling of interval variables and the addition of one interaction term.

Using statistical tests, the model as a whole was determined to exhibit some lack of fit. Closer analysis indicated that the model does perform well across many levels of estimated probability of DEP loss. Using USAREC's red, amber, green DEP loss risk classification system, the model appears to have significant predictive powers. The model also performed well using this classification system for a validation data set. It is concluded that this fitted model could prove useful in supplementing the field experience of the recruiter in predicting DEP loss risk of individual recruits.

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I. INTRODUCTION

The United States Army Recruiting Command (USAREC) utilizes the Delayed Entry Program (DEP) as an important management tool in ensuring the US Army receives a continuous flow of recruits. The Delayed Entry Program provides benefits to the recruit and the Recruiting Command alike. A major shortcoming of this program is that some newly contracted recruits in the DEP pool do not enlist. This attrition process is costly in recruiting resources and potentially results in training seats being unfilled. This research models the DEP loss process in an attempt to identify contracts with relatively high risks of DEP loss.

A. DELAYED ENTRY PROGRAM DESCRIPTION

The DEP is an enlistment program which allows an individual to delay entry onto active duty for a period of up to 365 days. It is best thought of as a reservation system. Qualified applicants are allowed to contract for enlistment at a specified time, for particular training, and a guaranteed job, for an agreed upon time of service [Ref. 1]. The recruiter keeps in close contact with the DEP member to help ensure that he remains mentally and physically qualified for enlistment, and that he maintains his desire to enlist. DEP management is any activity that promotes this accession goal

and includes funded and unfunded DEP functions, optional military training or instruction, and other activities. DEP management is quite similar to the initial recruiting process in that the initial contract is continuously resold while the recruit is in the DEP. [Ref. 2]

The day in which a young person could walk into the Recruiting Office, sign up, and ship out is gone. With the arrival of the Drug and Alcohol Testing (DAT) in June 1988, DEP is the vehicle in which all recruits enter active duty.

B. DEP BENEFITS

The DEP provides benefits for both the recruit and USAREC. The DEP allows the recruit to lock in training, schooling and an assignment, many months in advance. A recruit in high school can make definitive plans for the future early in his senior year. The DEP also allows the recruit a wider range of available assignments. The recruiter is able to project out one year for available assignments. This is especially valuable for the top quality recruit who qualifies for all assignments.

The DEP provides benefits to the US Army because it allows for efficient resource management in a business that tends to be extremely seasonal. The DEP aids in future planning of training availability and personnel requirements. Recruiters are able to focus on high quality recruits rather than meeting short term accession goals. US Navy research efforts indicate

that a large DEP pool may actually assist recruiting [Ref. 1]. This may be due to the promotion incentives offered to DEP members who refer candidates who then enlist. In effect, every DEP member becomes a recruiter, representing the US Army in the high schools and work places, creating a type of recruit network.

Another byproduct of the DEP is that it may result in lower first term attrition. One study conducted for the US Army in 1985 concluded that the longer the recruit was in the DEP the more likely he was to successfully complete his term of service. The theory of this study is that a recruit who has more time to evaluate his contract decision, and then accesses onto active duty, will be more inclined to fulfill his contractual obligation [Ref. 3]. A related theory is that someone who survives a longer period in the DEP may be more committed to begin with, so that a portion of the total attrition occurs in the DEP rather than after enlistment.

C. DEP SHORTCOMINGS

The DEP is not without its costs to USAREC. During the period a recruit is in the DEP, he may attrite or become a DEP loss. A DEP loss may be the result of a myriad of reasons ranging from death or serious injury, to apathy, to joining another service or National Guard. During the last ten years, DEP loss has grown from 7% upwards to 13% in FY 89. As of 1 December 1990, approximately 15% of all contracts signed in FY

90 resulted in DEP losses.¹ Figure I depicts the trend over the last 20 quarters. Large DEP losses significantly contributed to USAREC not meeting its accession goals in October and November 1990, the first time in over seven years.

USAREC Regulation 601-95 states, "DEP loss has a major impact on mission accomplishment." A DEP loss must be replaced by a new recruit, demanding valuable recruiter resources and time. If a DEP loss occurs shortly before the accession date, a training seat could remain unfilled. With smaller defense budgets, the US Army cannot afford to under utilize its training resources. In the last year, USAREC reports that recruiters are finding they must make on the average 12 contacts with potential recruits, versus an average of 8 in previous years, to secure one enlistment [Ref. 4]. This indicates that it may become even more difficult to recruit replacements for DEP losses in the future.

D. CURRENT USAREC DEP SYSTEM

USAREC's command goal is to reduce DEP loss to six percent or less of all signed contracts [Ref. 2]. As Figure 1 indicates, this goal has not been reached in any of the last 20 quarters and only during two, one month periods in FY 90. USAREC Regulation 601-95 outlines many approved techniques to

¹ As of 1 December 1990, approximately 80% of all contracts signed in FY 90 had resulted in accessions or DEP losses. The remaining recruits were still awaiting accession onto active duty or DEP loss.

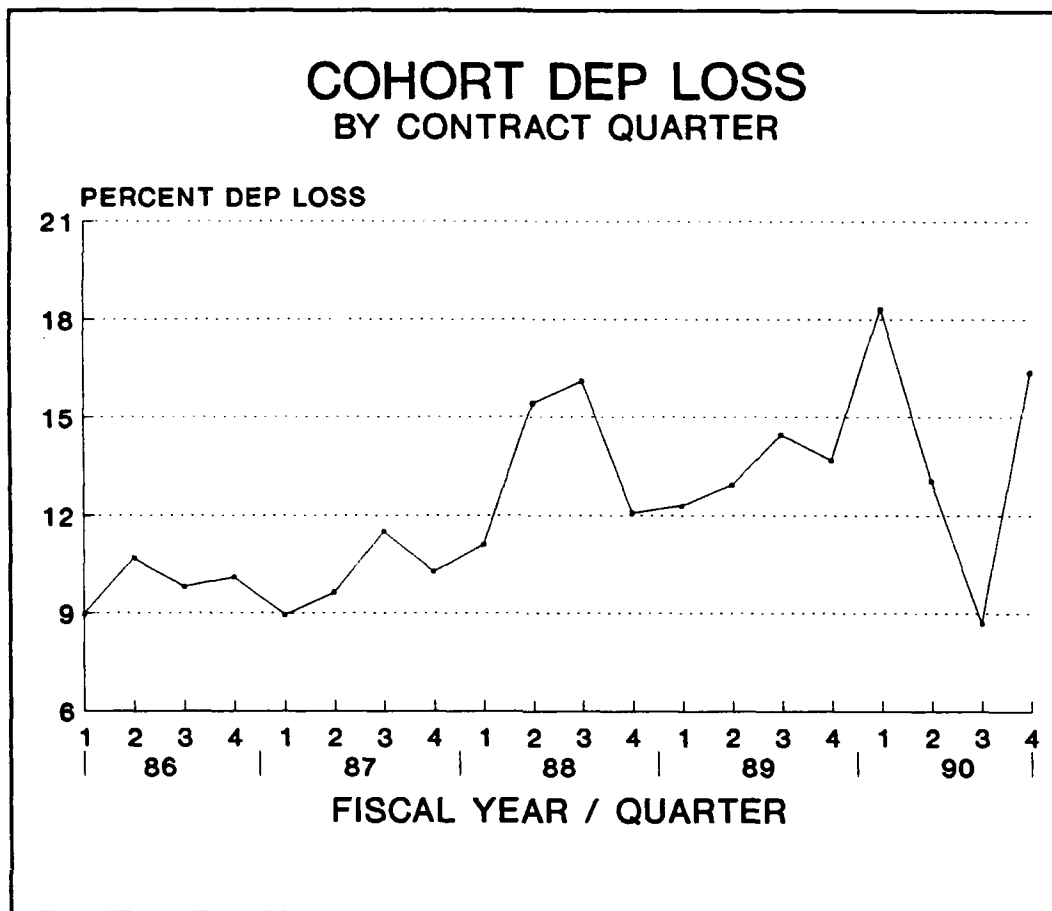


Figure 1 Cohort DEP Loss by Quarter FY86 - FY90

help avoid DEP losses. These include: minimum standards for number of times a recruiter contacts a DEP member, DEP incentive programs, and funded DEP events. Currently, recruiters rely only on their experience in the field to categorize their recruits in the DEP as being high, medium, or low DEP loss risks. Recruiters are required to report to their chain of command monthly their subjective opinion as to the risk status of their DEP members using the following coding scheme:

- Green: Indicates the DEP member remains motivated to access onto active duty and there are no foreseeable problems.
- Amber: Indicates there may be potential problems with either motivation or qualification to access onto active duty.
- Red: Indicates a problem. This DEP member for whatever reason is a probable or certain DEP loss.

This system of using the field expertise of the recruiter and his personal knowledge of each DEP member appears to be valuable. USAREC could potentially augment this system with quantitative techniques or models to better assist in predicting DEP losses.

Chapter II summarizes the goals of this research and the general approach that was taken. Chapters II and III concern selection of candidate explanatory variables and initial analysis of these variables. Chapter V details the building of the model and its refinement. The last three Chapters, VI through VIII assess the model's fit, explores a possible model use, and finishes with recommendations and conclusions.

II. RESEARCH GOALS

A. APPROACH

USAREC maintains a large historical database containing extensive information on every contract that is signed throughout the Command. The approach of this study was to use this database and other readily available USAREC data resources to develop a DEP attrition model. This approach has resulted in quantitative models that should be useful to USAREC as supplements to field expertise. Research focused on providing the recruiter in the field with a system to complement his subjective opinion as to the risk of a DEP member becoming a loss. Though certain conclusions were drawn regarding USAREC DEP policies, this was not the emphasis.

B. PREVIOUS RESEARCH EFFORTS

Research was conducted on the DEP loss process during the 1980's. Current USAREC DEP tracking and analysis is aggregated at the Recruiting Battalion level to provide early warning in case accession goals are in jeopardy. Several studies have used time series analysis to predict the rate in which DEP loss occurs [Ref. 5]. A shortcoming with this approach is it assumes DEP losses occur on the date reported in the database. These dates are then used for developing models of DEP loss rates. In actuality, this date merely reflects when the

recruiting chain of command officially reported the loss. The actual date in which the recruit decided to leave the DEP could have been months prior.

Individual contract level models have been developed but focused on only those contracts signed by high school seniors and graduates in the highest mental category.² The most recent year of recruiting data used in developing these models was FY 88. Our research used data covering all non prior service contracts signed in FY 86 through FY 90. We examined contributions of the following new areas:

- The 17 - 21 year old population in each Recruiting Battalion's region
- Military/civilian pay ratios for the Recruiting Battalion
- Total number of Department of Defense recruiters in the Recruiting Battalion's region
- Recruiting Battalions
- Career Management Field (CMF) of contract
- Renegotiation status of the contract
- Number of recruiters per contract in the Recruiting Battalion (contract density)
- Brigade (local) and national advertising budgets

The inclusion of these new variables may potentially result in better predicting power as compared to already

² Nelson, 1988, Army Research Institute and Celeste, 1989, WESTAT.

existing models. Additionally, many officials at USAREC believe the combination of a declining advertising budget, fewer recruiters in the field, and a dwindling 17 - 21 year old population have significantly impacted all recruiting operations over the last five years.³ All three of these concerns are addressed in the models developed here.

³ This information was obtained during interviews with USAREC personnel from 18 November through 21 December 1990 during an experience tour at USAREC Headquarters, Fort Sheridan, IL.

III. VARIABLE DEVELOPMENT

There are many similarities between the initial selling of a contract by a recruiter and the reselling that goes on with a member of the DEP. The recruiter must periodically meet with the DEP member and resell him on his initial contract. This recruiting effort receives command emphasis throughout USAREC. For this reason, many of the same variables used in contract production models were analyzed for applicability in a DEP loss model. Explanatory variables can be described as being either individual, demographic, or policy factors.

A. INDIVIDUAL FACTORS

Individual factors are the personal characteristics of the DEP member. Table I shows the variables that were considered for inclusion and their source. These variables represent the characteristics of the recruit on the day that the contract was signed. USAREC updates the EDUC variable as the DEP member's education status changes. Therefore, this value was obtained from a previous education code in the database. The EDUC variable includes four classes. All education codes indicating education levels above high school were aggregated

Table I INDIVIDUAL FACTORS TO BE ANALYZED

VARIABLE	DESCRIPTION	SOURCE ¹
AGE	AGE IN YEARS ON CONTRACT DATE	USAREC MM
MARITAL	MARITAL STATUS	USAREC MM
SEX	MALE OR FEMALE	USAREC MM
RACE	WHITE, BLACK, HISPANIC, ASIAN, OTHER	USAREC MM
EDYRS	YEARS OF EDUCATION	USAREC MM
EDUC	STATUS OF HIGH SCHOOL DIPLOMA, EITHER IN HIGH SCHOOL, NON GRADUATE, DIPLOMA GRADUATE, OR OTHER TYPE OF GRADUATE	USAREC MM
AFQT	ARMED FORCES QUALIFICATION TEST SCORE	USAREC MM
CONDATE	DATE IN WHICH CONTRACT WAS SIGNED	USAREC MM
DEPEND	NUMBER OF DEPENDENTS	USAREC MM

NOTE: 1. USAREC MM is the Minimaster database maintained at USAREC containing information on all contracts signed during a fiscal year.

into one class. Likewise, the many types of high school graduates other than regular diploma graduate were aggregated into one class. RACE was aggregated into the four numerically largest races. The category OTHER included the remaining less populace races.

B. DEMOGRAPHIC FACTORS

Demographic factors are the characteristics of the geographic region in which the recruit lived when the contract was signed. Table II describes these variables and their sources. Quarterly data were used to calculate these variables. When monthly data were available, as in the MISSION and DOD variables, the quarter's mean was used. The level of

Table II DEMOGRAPHIC VARIABLES TO BE ANALYZED

VARIABLE	DESCRIPTION	SOURCE¹
UNEMP	LOCAL UNEMPLOYMENT RATE IN THE RECRUITING BATTALION IN THE QUARTER IN WHICH THE CONTRACT IS SIGNED	SUPERSITE
BN	RECRUITING BATTALION (54 CONSIDERED)	USAREC MM
MISSION	RECRUITING BATTALION RATIO: <u>MILITARY AVAILABLE 17-21 OLD</u> NUMBER OF CONTRACTS	USAREC MM / BERLIANT
PAYRATE	RECRUITING BATTALION RATIO: <u>CIVILIAN MEDIAN INCOME</u> E-2 UNDER 2 YEARS PAY	SUPERSITE / US ARMY FINANCE
DOD	RECRUITING BATTALION RATIO: <u>MILITARY AVAILABLE 17-21 OLD</u> MEAN NUMBER OF DOD RECRUITERS	USAREC PAE

NOTE: 1. Supersite is the DOD Manpower Data Center's Supersite Demographic Database; USAREC MM is the USAREC Minimaster database; Berliant is an Army Research Institute study [Ref. 6]; USAREC PAE is the USAREC Program Analysis and Evaluation Directorate

the demographic variable is the Recruiting Battalion. PAYRATE was not indexed for inflation. Since civilian median income and E-2 pay increased separately, the ratio of these two incomes was the explanatory variable used. Of the 55 Recruiting Battalions, the San Juan Battalion was eliminated from the study due to lack of demographic data.

The MISSION variable was used to represent contract density in each region. A large value indicates a high output Recruiting Battalion relative to their available population base. It also might indicate a propensity of candidates in the region to join the US Army.

The DOD variable was included to allow for the presence of Department of Defense recruiters. Small values in this variable would represent competition from the other services for the available recruit population. Many USAREC officials postulate that there is an increased propensity to join the US Army when any service is well represented in a region.

C. POLICY FACTORS

Policy factors are those characteristics of the contract that are dependent on USAREC policies current at the time the contract was signed. Table III describes these factors and their sources. Note that the TIMEDEP variable is the contracted time to be in the DEP, not the actual time. As with

Table III POLICY VARIABLES TO BE ANALYZED

VARIABLE	DESCRIPTION	SOURCE ¹
TIMEDEP	TIME CONTRACTED TO BE IN THE DEP	USAREC MM
BONUSAMT	AMOUNT OF BONUS (IF ANY)	USAREC MM
RENO	BINARY VARIABLE INDICATING IF A CONTRACT RENEGOTIATION OCCURRED WHILE IN THE DEP	USAREC MM
ACF	INDICATES IF THE RECRUIT IS AN ARMY COLLEGE FUND TAKER	USAREC MM
CMF	CAREER MANAGEMENT FIELD (31 AVAILABLE)	USAREC MM
TERM	TERM OF CONTRACTED ENLISTMENT	USAREC MM
CONPER	CONTRACTS PER RECRUITER FOR THE QUARTER IN THE RECRUITING BATTALION	USAREC PAE
BDEADV	BRIGADE LOCAL ADVERTISING BUDGET FOR THE FISCAL YEAR AND RECRUITING BRIGADE	USAREC APAD
NATADV	NATIONAL ADVERTISING BUDGET FOR FISCAL YEAR	USAREC APAD

NOTE: 1. USAREC MM is the Minimaster database; USAREC PAE is USAREC Program Analysis and Evaluation Directorate; USAREC APAD is USAREC Advertising and Public Affairs Directorate.

demographic factors, CONPER is the quarterly mean with respect to both number of contracts and the number of recruiters. Data were aggregated at the Recruiting Battalion level. The BDEADV and NATADV advertising variables were indexed to FY 86 dollars using USAREC Advertising and Public Affairs Directorate advertising price indexes.

D. DATABASE

1. Sources

As shown in Tables I through III, the USAREC Minimaster database was the primary source of data for this model development. These records are year end pictures of all recruiting contract activity during the fiscal year. Contracts are represented on successive fiscal year Minimaster files until the contract is closed by either accession or DEP loss. An example: a contract signed in FY 86 with an accession or DEP loss in FY 87 would be on both Minimaster 86 and 87 databases. Minimaster 86 would indicate this as an open record. Then, Minimaster 87 would contain the accession status of the contract.

Minimaster 86 did not include the bonus amount of the contract but only whether one was received. Using historical bonus information from USAREC Recruiting Operations Directorate, these data were reconstructed.

Information regarding US Army and DOD recruiter field strength and advertising budgets was obtained from

directorates at USAREC Headquarters. DOD Manpower Data Center (DMDC) provided the employment and civilian median income information for each Recruiting Battalion. DMDC subcontracted to provide USAREC with a Supersite system which aggregates county level economic data to Recruiting Battalion level [Ref. 7]. The source for the 17 - 21 year old prime recruiting market at the battalion level was a 1989 Army Research Institute study conducted by Kenneth R. Berliant [Ref. 6].

2. Database Development

Statistical Package for Social Scientists (SPSS) was used for screening, sorting, and merging the Minimaster records in preparation for model development. This statistical package was used because of its widespread use at USAREC. This should assist any future updating of the model as data become available. Table IV details the results of the database after screening for unwanted records and data errors. A total of 247,592 records were eliminated as being open, prior service, from the San Juan Battalion, or contracts signed before FY 86. Open records were not closed out in the given fiscal year as a result of accession or DEP loss. They were then repeated and closed out in the following fiscal year. Approximately 3.5% of the records were eliminated due to coding errors in the data. Due to the large size of the database, 715,668 records, it was not felt that this would significantly bias the data or the analysis results. Analyses indicated that the eliminated

records possessed approximately the same percentage of DEP losses as the entire contract population.

After the Minimaster files were screened and concatenated, the demographic and policy variables containing quarterly values were merged to create the final large database. There were 689,278 contract records available, each containing DEP loss status and values of 24 candidate explanatory variables.

Table IV RESULTS OF DATABASE SCREENING

RECORDS INITIALLY AVAILABLE		NUMBER
MINIMASTER FY86		208,504
MINIMASTER FY87		206,326
MINIMASTER FY88		192,048
MINIMASTER FY89		193,682
MINIMASTER FY90		162,700
SUBTOTAL		963,260
RECORDS ELIMINATED		
OPEN RECORDS ¹		112,293
PRIOR SERVICE RECORDS		66,201
CONTRACTS SIGNED IN FY85		60,680
RECORDS FROM SAN JUAN BATTALION		8,418
SUBTOTAL		247,592
RECORDS ELIMINATED DUE TO ERRORS IN DATA		
NUMBER OF DEPENDENT ERRORS		12,467
BATTALION / BRIGADE DESIGNATION ERRORS		4,846
TERM OF SERVICE ERRORS		2,195
NUMBER OF YEARS EDUCATION ERRORS		1,907
CONTRACT YEAR / MONTH ERRORS		1947
PROJECTED ACCESSION YEAR / MONTH ERRORS		1716
BIRTH YEAR / MONTH ERRORS		579
TIME IN DEP ERRORS		512
MILITARY OCCUPATION SPECIALTY ERRORS		130
ARMED FORCES QUALIFICATION TEST ERRORS		91
SUBTOTAL		26,390
RECORDS AVAILABLE FOR ANALYSIS		
TOTAL		689,278

NOTES: 1. Open records have not been closed out in the given fiscal year as a result of accession or DEP loss. They are then repeated and closed out in the following fiscal year.

IV. DATA SUMMARY

A. DEP LOSS TRENDS

An initial analysis with data in the DEP loss database concerned possible seasonal effects on DEP losses during the Recruiting year. Two methods were used to calculate the DEP loss percentages. The first method, shown in Figure 2, was by contract cohort. Contracts for the months of FY 86 through FY 90 were tracked as a cohort. Percent DEP loss is the

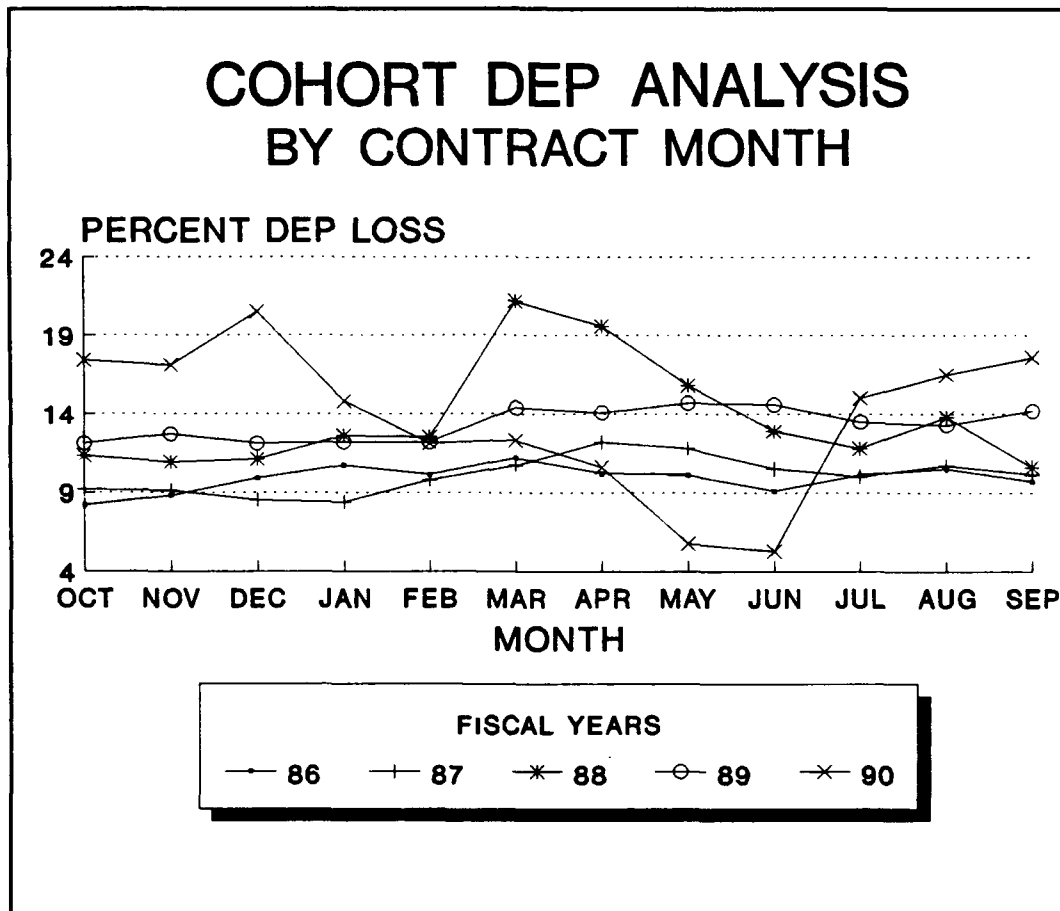


Figure 2 Contract Cohort DEP Loss Analysis

percentage of this cohort that resulted in a DEP loss. There did not appear to be any strong reoccurring seasonal trend. The significant increase in DEP loss in the spring of 1988 was a result of a one time DEP forgiveness program instituted by USAREC in response to accession cutbacks.

The second method for examining DEP loss was by accession cohort. The accession status of all recruits that were projected to access in the months of FY 86 through FY 90 were tracked. The percent of the accession cohorts that resulted in DEP loss is depicted in Figure 3.

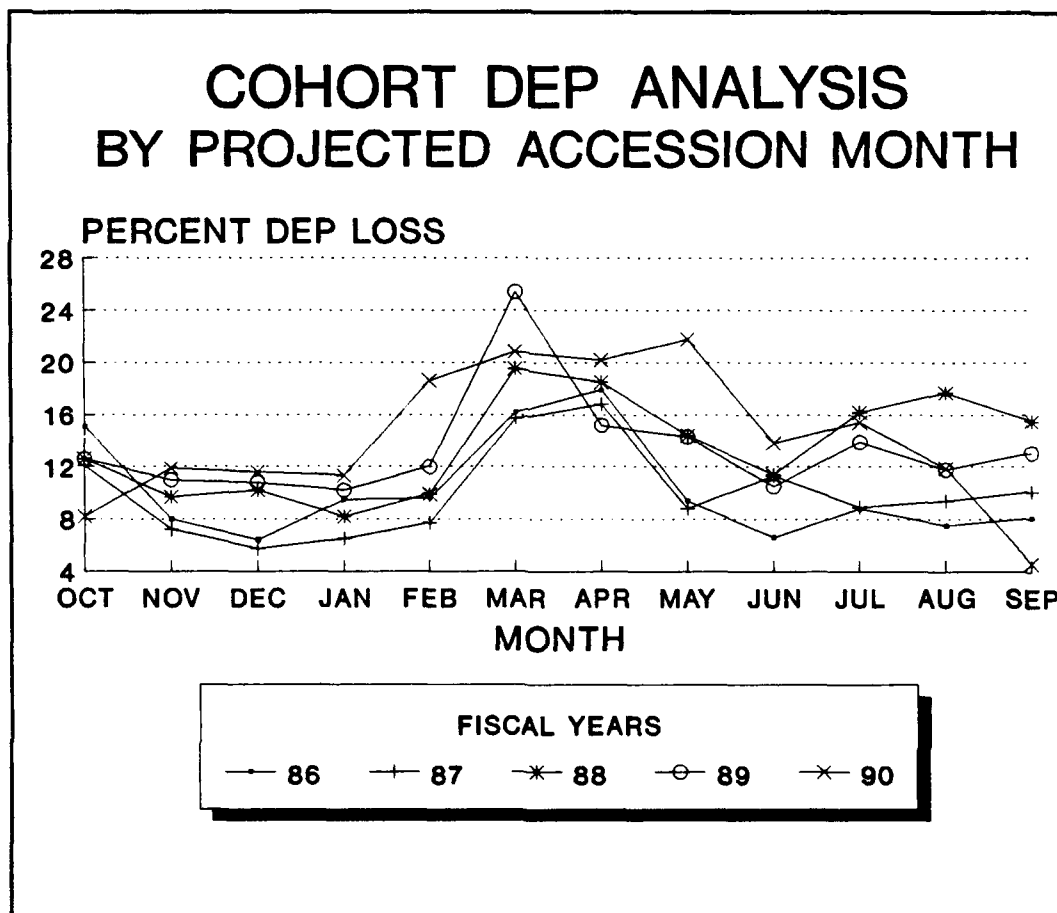


Figure 3 Projected Accession Cohort DEP Loss Analysis

There appeared to be a trend for higher DEP losses in spring, March through May, during each of the five fiscal years. This may have been a result of high school seniors who signed contracts early in the year. They then may have changed either education or career goals in the spring. Since there appeared to be a seasonal trend, a dummy variable for projected accession month was included in the model development.

B. INTERVAL VARIABLES

Fourteen of the 23 initial explanatory variables were interval (scale) variables. Using SPSS, initial analyses were conducted to determine if there were significant differences between the two groups, accession and DEP loss, with respect to these variables. The mean values for the two groups are listed in Table V. The T-test is used as a basis for rejecting or failing to reject the null hypothesis that the two sample means are equal. Due to the large sample size (689,278), the T-test does not require that the samples come from a Normal population. With T-test significance levels below .00005 for these interval variables, there is less than .005% chance that such sample means would be this different if the population means were equal. We acknowledge that with this large sample that the null hypothesis will almost always be rejected. Though statistical significance is indicated, we believe there is practical significance in the difference of these means.

Table V INTERVAL VARIABLE ANALYSIS

<u>INTERVAL VARIABLE</u>	<u>VARIABLE DESCRIPTION</u>	<u>ACCESSION₃ CONTRACTS</u>	<u>DEP LOSSES³</u>
AGE	AGE IN YEARS ON CONTRACT DATE	19.9572	19.7859
EDYRS	YEARS OF EDUCATION	12.0702	11.6019
AFQT	ARMED FORCES QUALIFICATION TEST PERCENTILE SCORE	58.6334	59.7147
TERM	TWO THROUGH SIX YEARS OF CONTRACTED SERVICE	3.539	3.5922
BONUSANT	CONTRACT BONUS AMOUNT (IF ANY)	318.97	283.27
DEPEND	NUMBER OF DEPENDENTS	.1782	.0820
TINEDEP	TIME CONTRACTED TO BE IN THE DEP	3.973	5.898
UNEMP	LOCAL (BN) UNEMPLOYMENT RATE AT TIME OF CONTRACT	6.355	6.06
MISSION ¹	RATIO: MILITARY AVAIL 17-21 YEAR OLD (BN) NUMBER OF CONTRACTS (BN)	394.65	412.83
PAYRATE ¹	RATIO: CIVILIAN MEDIAN INCOME (BN AREA) MILITARY PAY (E-2 UNDER 2 YEARS)	2.872	2.937
CONPER ¹	RATIO: NUMBER OF CONTRACTS (BN) MEAN # OF RECRUITERS ASSIGNED (BN)	8.24	7.58
DOD ¹	RATIO: MILITARY AVAIL 17-21 YEAR OLD (BN) MEAN # OF DOD RECRUITERS (BN)	767.85	760.3
BDEADV ²	BRIGADE LOCAL ADVERTISING BUDGET FOR THE FISCAL YEAR	890,607	872,658
NATADV ²	USAREC NATIONAL ADVERTISING BUDGET FOR FISCAL YEAR	65,093,198	63,654,535

NOTES: 1. Variables are calculated using data for quarter in which contract was signed. 2. Variables are calculated for fiscal year in which contract was signed. 3. T-test significance less than .00005

The variable TERM is the only variable in which the practical significance appears questionable.

The mean values for these interval variables give some insight into the DEP loss contract holder, compared to those who access. The DEP loss is slightly younger and has fewer

years of education because he may be more likely to still be in high school. His AFQT score is higher than average contracts which may indicate more opportunities. His contract term of service is longer and he gets less than an average bonus amount. He has fewer dependents to worry about and is planning on spending much more than average time in the DEP awaiting accession onto active duty. The economic situation in his Recruiting Battalion region is better than average as indicated by lower unemployment and better civilian pay. There is less contract density in his Recruiting Battalion region. There are more DOD recruiters in his region than average. USAREC spends less on advertising in his region of the country.

The CONPER values appeared counter intuitive. The number of contracts per recruiter was lower for DEP loss contract holders. This may indicate that high mission recruiters tended to have less DEP losses. This phenomena may be due to USAREC's Recruiting Zone Analysis (RZA) that assigns recruiters and missions to Recruiting Battalions. This could indicate that high propensity regions as determined by RZA suffer less DEP losses.

As previously mentioned, the large database assisted in increasing the significance of these T-tests. This may have overemphasized their explanatory value as covariates in attrition models. Even so, these interval variables appeared

significant in the univariate analyses and were included as candidate explanatory variables in the modeling process.

C. CLASS VARIABLES

The remaining nine explanatory variables were categorical or class variables. Again, using SPSS, cross tabulations with Chi-Square tests were conducted to determine if DEP loss status was independent of the class variables. Table VI lists the first seven class variables and Appendix A, Tables XIII through XVI list the class variables with larger numbers of levels, Career Management Field (CMF) and Recruiting Battalion. The results of the Chi-Square tests indicated that all the class variables were highly significant. As with the interval variables, there is less than a .005% chance that such distributions would have occurred if DEP loss status was independent of these class variables.

Initial analyses indicated that marital status, sex, education level, and contract renegotiation status were the more significant explanatory class variables. Several of the CMF's and Recruiting Battalions appeared to be strong explanatory variables. CMF 00 had a 99.4% DEP loss rate. According to USAREC Recruiting Operations Directorate, this is not a valid CMF. It was used in FY 87 and FY 88 as a surrogate CMF for known DEP losses who were not officially dropped for an extended period. This use of CMF 00 freed the previously

Table VI CLASS VARIABLE ANALYSIS

<u>CLASS VARIABLE</u>	<u>VARIABLE DESCRIPTION</u>	<u>PERCENT ¹ ACCESSION</u>	<u>PERCENT ¹ DEP LOSS</u>
MARITAL	MARITAL STATUS TIME OF CONTRACT		
..MARRIED	9.6% MARRIED	10.3	4.56
..SINGLE	90.4% SINGLE / NOT MARRIED	89.7	95.44
SEX	MALE OR FEMALE		
..MALE	84.6% MALE	85.5	78.24
..FEMALE	15.4% FEMALE	14.5	21.76
RACE	FOUR LARGEST RACES AND OTHER		
..WHITE	70.1 % WHITE	69.6	73.6
..BLACK	24.4% BLACK	24.9	20.8
..HISPAN	2.3% HISPANIC	2.34	2.15
..ASIAN	1.2% ASIAN	1.2	1.05
..OTHER	2.0% OTHER / UNKNOWN	1.96	2.4
EDUC	EDUCATION CODE AT CONTRACT		
..SENIOR	29.7% IN SCHOOL	27.6	45.66
..NONGRAD	3.8% NON-GRADUATE HIGH SCHOOL	3.86	2.84
..DIPGRAD	62.5% DIPLOMA GRAD HIGH SCHOOL	64.4	48.1
..OTHGRAD	4.1% OTHER TYPE GRAD HIGH SCHOOL	4.14	3.4
ACF	ARMY COLLEGE FUND TAKER		
..TAKER	18.9% ACF TAKERS	19.04	17.63
..NOTAKER	81.1% NOT ACF TAKERS	80.96	82.37
RENO	RENEGOTIATION OF CONTRACT IN DEP		
..YESRENO	8.9% OF CONTRACTS RENEGOTIATED	8.22	13.95
..NORENO	91.1% NOT RENEGOTIATED	91.78	86.05
RECFY	RECRUITING FISCAL YEAR IN WHICH CONTRACT WAS SIGNED		
..86	26.5% SIGNED IN FY86	27.09	21.74
..87	24.1% SIGNED IN FY87	24.49	21.54
..88	19.0% SIGNED IN FY88	18.64	21.76
..89	20.3% SIGNED IN FY89	20.05	22.13
..90	10.1% SIGNED IN FY90	9.73	12.83
TOTAL ²	TOTAL CONTRACT PERCENTAGES	88.17	11.83

NOTES: 1. Cell difference significance less than .00005 Chi-square test. 2. Class variable analysis for Career Management Field (CMF) and Battalions see Appendix A, Tables XIII through XVI.

reserved CMF to be used for another contract. Rather than delete these records and loose the data, they were retained and dealt with during model development.

The results of the data assessment process justified inclusion of the 23 candidate explanatory variables. It also revealed that due to a seasonal trend, the projected accession month may be a strong explanatory variable. In our model development we attempted to use these 24 interval and categorical variables to predict DEP loss.

V. MODEL DEVELOPMENT

A. MODEL SELECTION

Empirically, the individual process of attrition from the DEP is represented by a dichotomous (binary) dependent variable which categorizes individuals either as accessions or DEP losses. The dependent variable definition is as follows:

$$Y_i = \begin{cases} 0, & \text{if individual } i \text{ accesses into the US Army} \\ 1, & \text{if individual } i \text{ is a DEP loss.} \end{cases}$$

Logit models are particularly well suited for dichotomous dependent variables because the logistic distribution lends itself to a meaningful interpretation. For notational purposes, the quantity:

$$\pi(X) = E(Y | X) \quad (1)$$

is used to represent the conditional mean of Y (DEP loss or accession) given the covariates X (explanatory variables).

The specific form of logistic regression model we used is as follows:

$$\pi(X) = E(Y|X) = \frac{1}{1 + e^{-g(X)}} \quad (2)$$

where $g(X)$ is the linear combination:

$$g(X) = B_0 + B_1x_1 + B_2x_2 + \dots + B_px_p \quad (3)$$

Where p is the number of covariates, x_i $i=1, \dots, p$ are the covariates, $X = (x_1, x_2, \dots, x_p)$, B_0 is the constant parameter, and B_i $i=1, \dots, p$ are the coefficient parameters.

The conditional mean in equation (1) is bounded in value by zero and one because of the fraction on the right hand side of equation (2). The usefulness of logistic regression is that the value, $\pi(X)$ may be interpreted as the probability of being a DEP loss ($Y=1$) given explanatory variables X , or $P(Y=1|X)$.

The logit transformation used in the fitting of the model is:

$$g(X) = \ln \left[\frac{\pi(X)}{1 - \pi(X)} \right] \quad (4)$$

This logit, $g(X)$ is linear in its parameters, is a continuous variable ranging in value from negative infinity to infinity. In order to estimate the value of $\pi(X)$ the parameters B_0 through B_p from equation (3) must be estimated using the method of maximum likelihood. [Ref. 8:p. 1-11]

The method of maximum likelihood uses the known covariates, X , to compute the estimates for B_0 through B_p so as to maximize the likelihood of obtaining the observed DEP loss status ($Y=0$ or 1). For a sample of size n , let y_i and

$X_i = (x_{1i}, x_{2i}, \dots, x_{pi})$ be the observed DEP loss status and vector of corresponding covariates for individual i , $i=1, \dots, n$. The likelihood (normal) equation resulting from the method of maximum likelihood for B_0 is :

$$\sum_{i=1}^n [y_i - \pi(X_i)] = 0 \quad (5)$$

Similarly, the normal equations for B_1 through B_p are:

$$\sum_{i=1}^n x_{ji} [y_i - \pi(X_i)] = 0 \quad ; j = 1, 2, \dots, p \quad (6)$$

The value of the vector $B=(B_0, B_1, \dots, B_p)$ given by the solution of these $p+1$ equations is \hat{B} , the maximum likelihood estimator for B . The values for the estimated probability of DEP loss are obtained from equations (2) and (3) by replacing B with \hat{B} . The estimated probability of DEP loss is denoted $\hat{\pi}$. An interesting result of equation (5) is the following:

$$\sum_{i=1}^n y_i = \sum_{i=1}^n \hat{\pi}(X_i) \quad (7)$$

The sum of the n observed values, y_i , is equal to the sum of the n predicted (expected) values, $\hat{\pi}_i$. This property of logistic regression was exploited in our assessment of the fit of the model. The solution of the normal equations above is found by an iterative process which has been programmed into

many available logistic regression computer software packages such as SPSS. The development and rationale for this model is given in Reference 8, pages 8-11.

B. MODEL BUILDING

SPSS, version 4.0, Logistic Regression Procedure was used to fit the model. This procedure required recoding of the class (categorical) variables. The following class variables with two levels were recoded (0,1) to indicate the presence of an attribute: MARITAL (married=1), SEX (female=1), ACF (yes=1), and RENO (yes=1). The other six class variables were recoded using the deviation coding scheme [Ref. 9:p. 55]. The number of new dummy variables required to represent a class variable with n levels is $n-1$. For the deviation coding scheme, if any of first $n-1$ levels of a class variable were present its corresponding new dummy variable was assigned the value of one. Otherwise, the new dummy variable was assigned the value of zero. In order to represent the presence of the n th level of a class variable, all the $n-1$ new dummy variables were assigned the value of negative one. This resulted in the creation of 105 new variables to represent RACE, EDUC, RECFY, BN, CMF, and PADDMO.

1. Variable Selection

SPSS's Logistic Regression procedure has the capability of executing stepwise variable selection. We used the forward stepwise selection as a basis for building our

model. The algorithm commenced with only the constant term in the model. Then, the variable with the lowest significance level for the Score statistic, provided it was lower than the chosen cutoff value P_{in} , was entered into the model. The Wald statistic's significance level was used to examine variables for possible elimination [Ref. 9:p. 56]. If the Wald statistic's significance level was higher than P_{out} , the variable was eliminated from the model. If no variable met the elimination criteria, the next eligible variable was added. This process continued until either a previously selected model was encountered or there were no further variables meeting the entry or removal criteria. Dummy variables representing the different levels of a class variable entered or were removed from the model as a group. [Ref. 9:p. 56-57]

Hosmer and Lemeshow [Ref. 8:p. 88] suggest the use of $P_{in} = .15$ and $P_{out} = .20$ as the best criteria for use in stepwise logistic regression using the Wald statistic. These criteria were aimed at selection of important variables for the model while also providing a parsimonious model.

Due to the computationally intensive nature of the iterative algorithms used to fit the model, combined with the numerous models built in forward stepwise regression, only a random 10% sample (68,962 cases) of the database was used in variable selection. This sample size required nearly 24 hours of CPU time on an Amdahl 5990-500 mainframe computer.

Variable selection resulted in all variables meeting the P_{in} / P_{out} criteria except two: these variables, MISSION and RECFY, were excluded from the model. The MISSION (contract density) variable's exclusion may have been a result of Recruiting Zone Analysis (RZA) used in assigning contract quotas to the Recruiting Battalion. RZA uses many of the same explanatory variables as our fitted model to determine each Recruiting Battalion's contract density. Therefore, this MISSION variable may not have provided the fitted model with information not already supplied by other explanatory variables. The non-selection of RECFY (Recruiting Fiscal Year) by the stepwise procedure may indicate that there was not a strong yearly influence on DEP loss that was not represented by one of the other chosen explanatory variables. This exclusion could prove to be helpful in future prediction uses of the model.

2. Interaction Terms

Univariate analyses and insight into the recruiting environment suggested that consideration of certain interaction terms was appropriate. A dozen interaction terms including combinations of RACE, EDUC, DEPEND, SEX, and MARITAL were considered. Only the RACE by EDUC interaction term was significant with respect to P_{in} in the stepwise procedure. The

inclusion of this interaction term did not result in the removal or entry of any previously selected or non-selected variables.

3. Scaling

The continuous scaled interval variables were checked for the assumption of linearity in the logit, $g(X)$, in equation (3). To this point all the interval variables, less MISSION, were identified as significant. Scaling assisted in obtaining the correct parametric relationship during the model refinement stage. We used the Box-Tidwell transformation to evaluate the need for scaling [Ref. 8:p. 90]. This simple technique adds a term of the form $x \cdot \ln(x)$ to the model for each continuous scaled interval variable. If the coefficient of these new variables appeared significant, there was evidence of non-linearity in the logit.

This technique resulted in six of the thirteen selected class variables, EDYRS, TIMEDEP, AGE, UNEMP, CONPER, and DOD indicating possible non-linearity. This technique could not be used for BONUSAMT and DEPEND because they included many values of zero. Therefore, these two variables were also included for further analysis.

A technique proposed by Hosmer and Lemeshow [Ref. 8:p. 90] was used in identifying the need to introduce new, higher-order variables in the model as a scaling method for those variables indicating possible non-linearity. The range of each

of these independent continuous interval variable was broken into groups and treated as a class (categorical) variable. Each case was assigned to the categorical class that represented its range in the original interval scale. The group representing the lowest scaled values served as the referent group. A model was fit to the same 10% random sample of the database using univariate logistic regression with only the one categorical variable. We then plotted the estimated coefficients for the levels of the categorical variable versus the group midpoint values from the initial interval scale. We chose the most logical shape for the scaling of the independent variable.

Figure 4 illustrates the results of using this technique on EDYRS (years of education). The unusual shape of the curve suggested that those in the DEP with eleven years of education had a higher probability of becoming a DEP loss. Likewise, DEP members with substantially more or less than eleven years of education appear to be at a greater risk of DEP loss relative to those with only several years more or less than eleven years of education.

We created a new variable, EDYRS2, representing $|EDYRS - 11|$, the distance from eleven years education. Model log-likelihood, covered in more detail in Chapter 6, was used to compare the improvement of introducing new higher order terms. The larger the model log-likelihood statistic, the more likely that if the fitted model is the correct model the

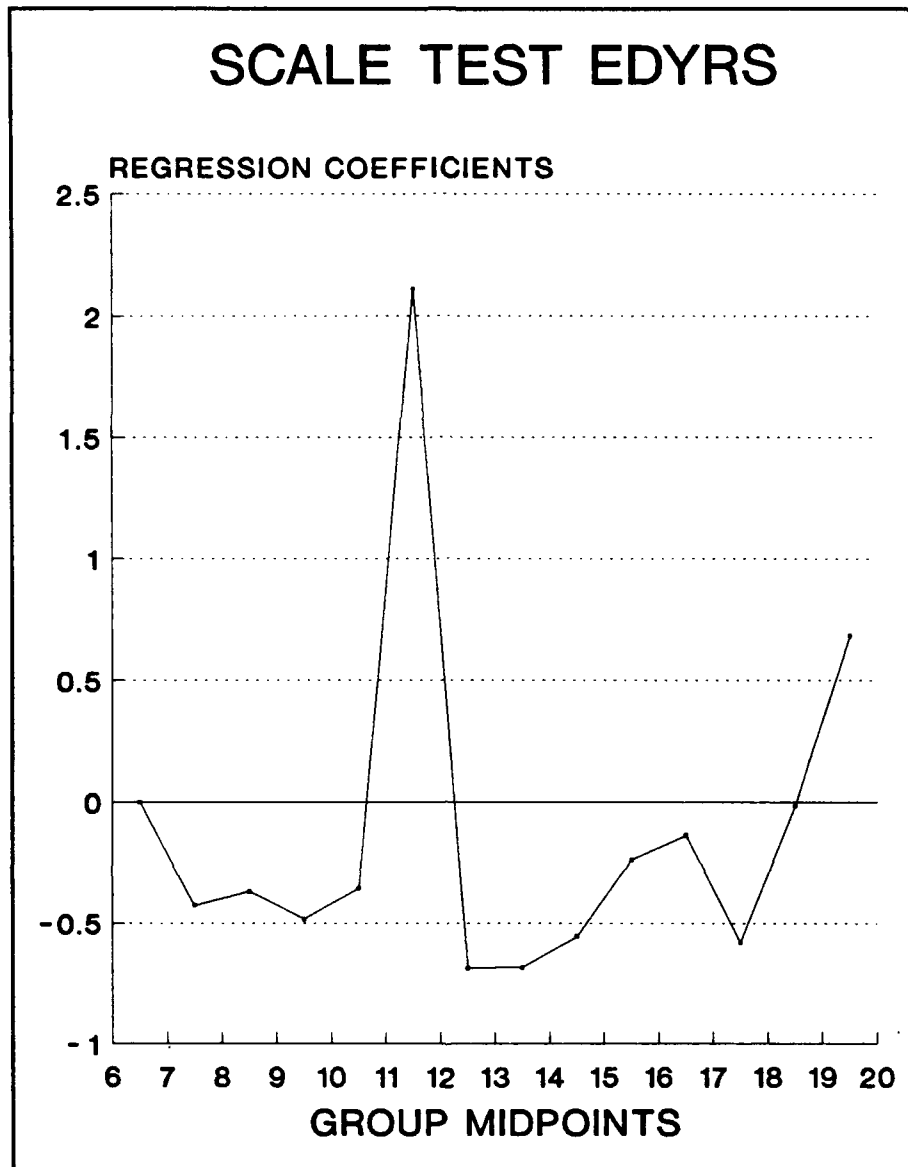


Figure 4 Hosmer-Lemeshow Scale Analysis on EDYRS

observed results would be obtained given the estimated parameters, \hat{B} . Univariate analysis indicated that EDYRS2 alone more than doubled the model log-likelihood over EDYRS by itself.

The same Hosmer-Lemeshow grouping technique was used for EDYRS2 to determine the need for introduction of higher order terms. Figure 5 depicts this new assessment. This curve appeared to be quadratic in the logit. A quadratic term, $EDYRS22 = (EDYRS2)^2$ was added to the model. The model containing EDYRS2 and EDYRS22 doubled the model log-likelihood again and was more than four times larger than the model containing EDYRS alone. Similar analyses were conducted on the

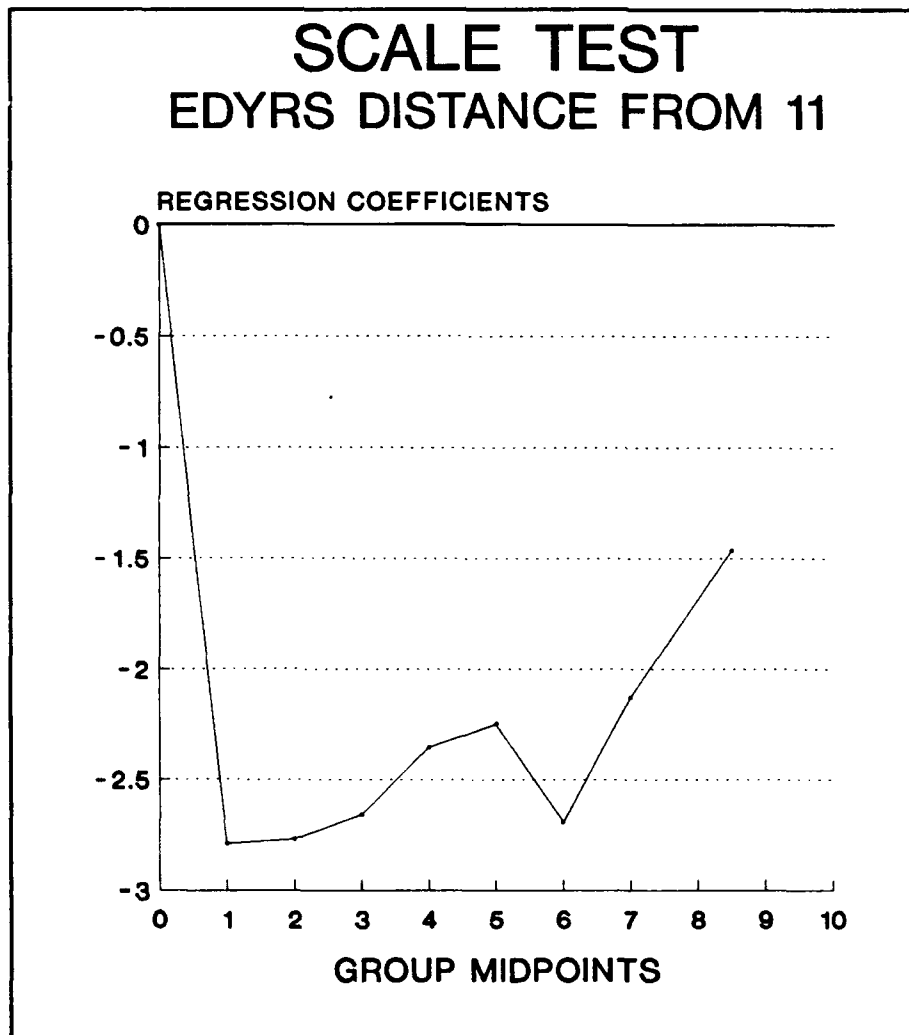


Figure 5 Hosmer-Lemeshow Scale Analysis on EDYRS2

other seven continuous variables for which non-linearity in the logit was suspected. Five of these seven assessments resulted in the scaling depicted in Table VII.

As a result of the addition of these higher-order terms, the variables BONUSAMT, DOD, DOD2, and DOD3 were eliminated from the model using backward stepwise elimination. The same values $P_{in} = .15$, $P_{out} = .20$ as in forward stepwise selection were used.

Table VII RESULTS OF HOSMER-LEMESHOW SCALING

ORIGINAL VARIABLE	SCALING	NEW VARIABLES	IMPROVEMENT RESULTS ¹
TIMEDP	CUBIC	TIMEDP2 = (TIMEDP) ² TIMEDP3 = (TIMEDP) ³	3.6 %
AGE	CUBIC	AGE2 = (AGE) ² AGE3 = (AGE) ³	1690 %
DEPEND	CUBIC	DEPEND2 = (DEPEND) ² DEPEND3 = (DEPEND) ³	31.3 %
CONPER	QUADRATIC	CONPER2 = (CONPER) ²	28.8 %
DOD	CUBIC	DOD2 = (DOD) ² DOD3 = (DOD) ³	445 %

NOTES: 1. Improvement is the percent increase in the model log-likelihood of the fitted model containing the new higher-order variables over a fitted model containing only the original variable.

C. MODEL EXECUTION

The final DEP loss model contained 23 interval scaled variables, five categorical (class) variables represented by 101 dummy variables, one interaction term with 12 levels, and the constant term. The total number of coefficients estimated, components of the B vector, was 136. Table VIII and Appendix A, Tables XVII through XX contain the variables in the final model, their estimated coefficients, \hat{B}_i and their significance levels based on the Wald statistic. A 25% sample (170,685 cases) was used for estimating the final model's coefficients. Estimation of B with this sample size required the maximum available scratch workspace and almost 20 hours of CPU time on a Amdahl 5990-500 mainframe computer.

Table VIII RESULTS OF FINAL MODEL

VARIABLE	ESTIMATED COEFFICIENT \hat{B}_i	SIGNIFICANCE LEVEL
TIMEDEP	.4795	.0000
TIMEDEP2	-.0193	.0005
TIMEDEP3	1.7E-05	.955
AGE	.7221	.0067
AGE2	-.0137	.2147
AGE3	4.1E-05	.7842
EDYRS2	-4.6175	.0000
EDYRS22	.7342	.0000
SEX	.6336	.0000
NATADV	-5.5E-08	.0000
MARITAL	-.398	.0000
CONPER	-.0335	.0000
CONPER2	.001	.0006
DEPEND	-1.5442	.0000
DEPEND2	.9147	.0000
DEPEND3	-.1617	.0000
RENO	-.2474	.0000
UNEMP	-.0415	.001
AFQT	.0013	.0386
BDEADV	1.3E-07	.1065
PAYRATE	-1.3486	.0000
ACF	-.038	.1836
TERM	-.0426	.0022
EDUC	NOTE 1	.0000
RACE	NOTE 1	.0000
PADDNO	NOTE 1	.0000
BN	NOTE 1	.0000
CMF	NOTE 1	.0000
RACE by EDUC	NOTE 1	.0002
CONSTANT	-3.691	.1311

NOTES: 1. The estimated coefficients for these class variables were not presented in this table due to their large number of levels. They are located in Appendix A, Tables XVII through XX.

VI. ASSESSING MODEL FIT

A known problem with the use of logistic regression models is the difficulty in assessing the fit of the computed model. Concerning logistic regression, Dr. Steven Fienberg, says, "But as long as some of the predictors are not categorical, we cannot carry out an omnibus goodness-of-fit test for a model." [Ref. 10:p. 104]. Our fitted model contains 23 interval (non-categorical) variables. Even though we acknowledge this stated difficulty, we attempted to use several known methods to assess the fit of our model. We pursued this effort in the hopes of gaining insight into our model's strengths and weaknesses.

A. LOG-LIKELIHOOD

The SPSS software uses the log-likelihood method to assess the quality of fit of the logistic regression model. With this method, one determines the likelihood of the observed results as a function of the parameter estimates. Since this likelihood is a small value, between zero and one, -2 times the log of the likelihood is used ($-2LL$). Additionally, the reason $-2LL$ is used is that it is asymptotically Chi-Square distributed. A good model results in a high likelihood or, equivalently, a small value for $-2LL$. [Ref. 9:p. 52]

Under the null hypothesis that our theoretical model fits perfectly, the value $-2LL$ is from a Chi-Square distribution

with $N - p = 170,548$ degrees of freedom. Here, N is the number of cases in our 25% sample (170,685) and p is the number of parameters estimated (137). The log-likelihood assessment output from SPSS is depicted in Table IX.

Table IX MODEL LOG-LIKELIHOOD FROM SPSS

	CHI - SQUARE	DEGREES OF FREEDOM	SIGNIFICANCE
- 2LL	85,421.7	170,548	.0000
MODEL CHI - SQUARE	35,812.5	137	.0000

The extremely small significance level for - 2LL indicates our model is not a perfect model. The probability that such results would be obtained with the correct model is nearly zero. The model Chi-Square is used to test the null hypothesis that the coefficients of all the variables in the model are zero. The small significance level computed for the model Chi-Square indicates that not all of these coefficients are zero. As noted in the T-tests of Chapter IV, we acknowledge that since the sample size is so large, the null hypothesis that the coefficients are zero will almost always be rejected. Though the null hypothesis of perfect fit of the model was rejected, the null hypothesis that the coefficients are all zero was also rejected.

B. PEARSON CHI-SQUARE

Hosmer and Lemeshow [Ref. 8:p. 140-145] developed a method for assessing the fit of logistic regression models using a test statistic similar to the Pearson Chi-Square test statistic. The strategy entails grouping the cases by their estimated probabilities, $\hat{\pi}$. Due to our large sample size, we used 20 groups with approximately 8,543 cases per group. The first group contained the 8,543 smallest $\hat{\pi}$ values, the second group the next largest 8,543 values, and so on.

For the $y=1$ row, representing all contracts that resulted in DEP loss, the expected number of DEP loss contracts for each of the 20 groups was obtained by summing the estimated probabilities of DEP loss, $\hat{\pi}$ for all the members of each of the corresponding 20 groups. The observed values for each of the 20 groups in this row are the number of observed DEP loss contracts within the respective group ($y_i=1$).

With the $y=0$ row, representing all contracts that resulted in accession, the expected number of accessions for each of the 20 groups was obtained by summing one minus the estimated probability of DEP loss, $\hat{\pi}$ for all the members of each of the corresponding 20 groups. The observed values for each of the 20 groups in this row are the number of observed contracts that resulted in accession within the respective group ($y_i=0$). Table X displays the results of these calculations.

Table X HOSMER-LEMESHOW GOODNESS OF FIT TABLE

		LEVELS OF RISK				
		1	2	3	4	5
	# OF CASES	8545	8543	8543	8543	8543
ACCESSION STATUS	$\hat{\pi}(x)$ CUTOFF	.0045	.0112	.0173	.023	.028
$Y_i = 1$ DEP LOSS	OBSERVED	379	356	222	235	215
	EXPECTED	17.5	66.7	122.1	172.5	219.7
	TEST STAT	7463	1264	83	23.1	.103
$Y_i = 0$ ACCESSION	OBSERVED	8166	8188	8321	8308	8328
	EXPECTED	8527	8477	8421	8370	8323
	TEST STAT	15.3	9.9	1.2	.48	.003
		LEVELS OF RISK				
		6	7	8	9	10
	# OF CASES	8543	8543	8543	8543	8543
ACCESSION STATUS	$\hat{\pi}(x)$ CUTOFF	.0336	.0388	.044	.0495	.0555
$Y_i = 1$ DEP LOSS	OBSERVED	224	254	304	278	324
	EXPECTED	264.6	308.7	353.1	399.1	448.1
	TEST STAT	6.43	10	7.12	38.6	36.2
$Y_i = 0$ ACCESSION	OBSERVED	8319	8289	8239	8265	8219
	EXPECTED	8278	8234	8190	8144	8095
	TEST STAT	.2	.38	.31	1.9	2.0
		LEVELS OF RISK				
		11	12	13	14	15
	# OF CASES	8543	8543	8543	8543	8543
ACCESSION STATUS	$\hat{\pi}(x)$ CUTOFF	.062	.0696	.0787	.0903	.1067
$Y_i = 1$ DEP LOSS	OBSERVED	340	402	470	562	657
	EXPECTED	500.8	560.9	632.1	720.2	838.5
	TEST STAT	54.9	48.2	44.9	37.9	43.5
$Y_i = 0$ ACCESSION	OBSERVED	8203	8141	8073	7981	7886
	EXPECTED	8042	7982	7911	7823	7704
	TEST STAT	3.4	3.4	3.6	3.5	4.7
		LEVELS OF RISK				
		16	17	18	19	20
	# OF CASES	8543	8543	8543	8543	8545
ACCESSION STATUS	$\hat{\pi}(x)$ CUTOFF	.1304	.1707	.2524	.6144	1.0
$Y_i = 1$ DEP LOSS	OBSERVED	869	1125	1626	3097	7537
	EXPECTED	1007	1269	1759	3230	6588
	TEST STAT	21.4	19.1	12.6	8.86	597
$Y_i = 0$ ACCESSION	OBSERVED	7674	7418	6917	5446	1008
	EXPECTED	7536	7274	6784	5313	1957
	TEST STAT	2.8	3.3	3.3	5.3	2010

The Hosmer-Lemeshow goodness of fit statistic \hat{C} is defined as follows:

$$\hat{C} = \sum_{i=1}^{20} \frac{(\text{OBSERVED}_i - \text{EXPECTED}_i)^2}{\text{EXPECTED}_i (1 - \bar{\pi}_i)}$$

WHERE, $\bar{\pi}_i = \frac{1}{N_i} \sum_{j=1}^{N_i} \hat{\pi}_j$; $i=1, \dots, 20$; $j=1, \dots, N_i$

WITH N_i = NUMBER OF CASES IN GROUP i

Hosmer and Lemeshow demonstrated that if the fitted logistic regression model is the correct model then \hat{C} has an approximate χ^2 distribution with $20 - 2 = 18$ degrees of freedom. The critical value, $\chi^2_{(df=18)}(\alpha = .05)$ is 28.87. The group's contributions to the test statistic \hat{C} are displayed in Table X. These sum to a number much greater than 28.87. This indicates our model has significant lack of fit. An advantage of a summary test statistic like \hat{C} is that it provides insight into the models fit over the 20 levels of DEP loss risk [Ref. 8:p. 144]. This model appears to fit reasonably well for those individuals that access ($y_i = 0$) in all groups except the bottom 10% (first two groups) and the top 5% constituting the twentieth group. Though the model in its entirety does not fit well as measured by \hat{C} , there appears to be potential for using its relatively good fit in all of the groups, except for these extreme groups, for predictive purposes.

Figure 6 illustrates how this misfit in the first two, and the last group impacted the value of \hat{C} leading to rejection of

the hypothesis of model fit. With a perfect model, the 20 group means of the estimated probabilities of DEP loss, $\hat{\pi}$ would equal the corresponding relative frequencies of the numbers of observed values of DEP loss ($y_i = 1$), to within random error. This would be represented by the line $y = x$. The curve corresponding to the fitted model appears to differ from the line $y=x$ only for the extreme groups.

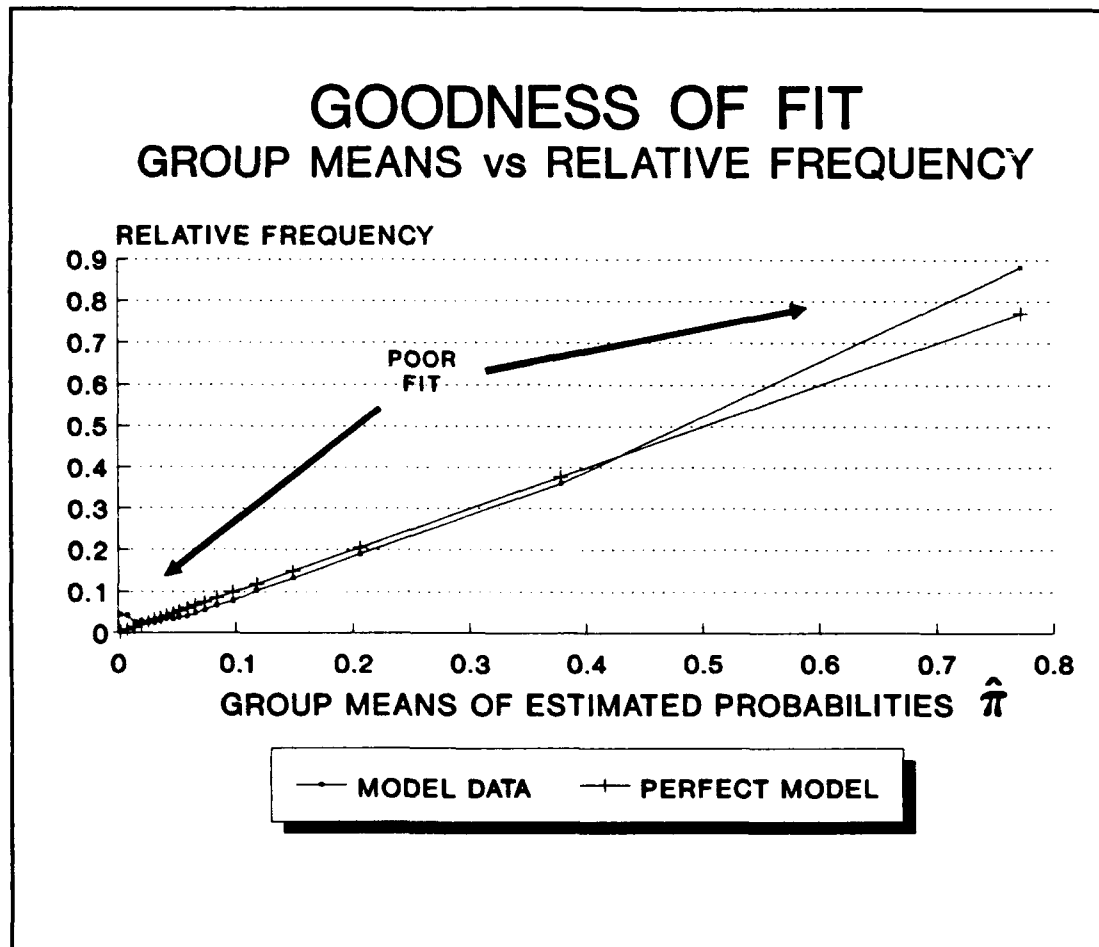


Figure 6 Hosmer-Lemeshow Goodness of Fit Plot

C. PREDICTION PLOT

An intuitive, alternative method for assessing the fit of the developed model is the prediction plot. Figure 7 shows smoothed histograms of the estimated probability of DEP loss, $\hat{\pi}$, for both the accession and DEP loss groups. The curve for the accession group is the plot of residuals; that for the DEP loss group is a plot of one minus the residuals. Relative frequencies were plotted due to the large quantity of accession cases in comparison to the number of DEP losses.

The developed model's lack of fit is evident in the rise of the DEP loss curve to the left of $\hat{\pi} = .4$ and the low values of the same curve on the extreme right. The large area under the DEP loss curve in the region of $.6 \leq \hat{\pi} \leq .9$ appeared to indicate that the model fit well for conditions giving estimated DEP loss probabilities in this region. However, the curve for accessions indicates the model accurately classified those that accessed. As desired, the majority of those that accessed were assigned a probability of DEP loss, $\hat{\pi}$, near zero.

Though two different statistical tests indicate that the entire model was significantly different from a perfect model, closer examination reveals that the model we developed appears to perform satisfactorily for the accession and DEP loss cases in most conditions. In the next chapter, we examine the model's effectiveness in a context of its intended use for DEP loss prediction.

PREDICTION PLOT ACCESSION & DEP LOSS

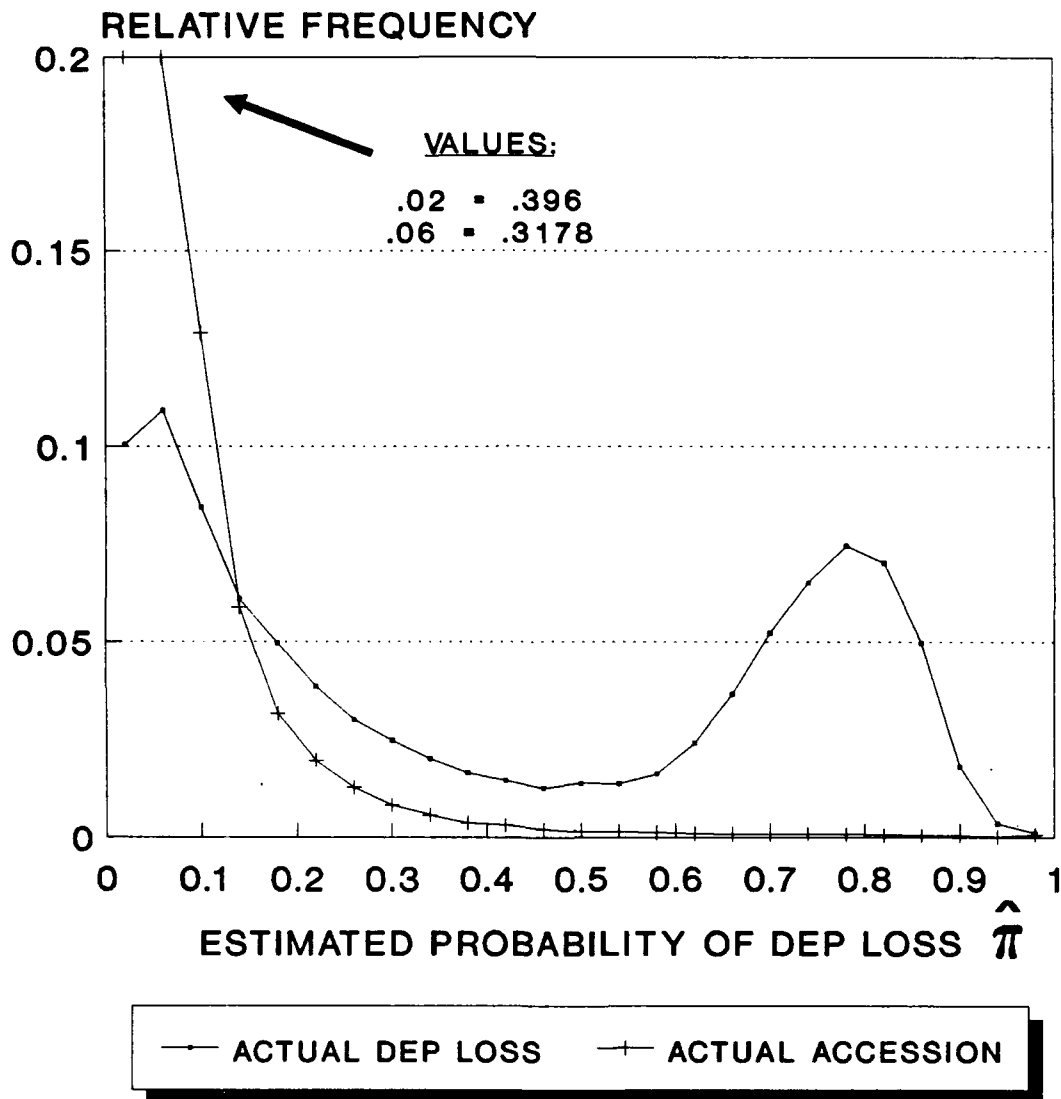


Figure 7 Prediction Plot for Accession and DEP Loss

VII. MODEL USAGE

A. RED, AMBER, GREEN

1. Classification Criteria

As mentioned in Chapter I, USAREC currently uses a red, amber, green coding scheme for recruiters to classify their DEP members according to perceived DEP loss risk. This model could provide a similar classification, augmenting the recruiters first hand knowledge of DEP members. This could prove especially helpful in classifying newly contracted DEP members, before the recruiter develops a relationship with the DEP member.

By computing and adjusting two threshold values of $\hat{\pi}$, we can control which of these three groups a DEP member is assigned. In determining these threshold values of $\hat{\pi}$, we used the following criteria. No more than one half of the DEP members would be placed in the amber group. This group is made up of the DEP members that the threshold rule will not classify as a predicted DEP loss or accession. The utility of the rule would be in question if it placed an unusually large number of DEP members in this group. USAREC could easily change this restriction on the proportion classified amber by adjusting the threshold values. The second criterion was to

maximize the model's accuracy in the classification of DEP members into the red and green categories.

2. GREEN Classification

The classification of a DEP member as green by the threshold value would alert the recruiter that this individual is not predicted to be a DEP loss. Figure 8 illustrates the power of the model with respect to the green category. We determined the predictive power of the fitted model is best represented by its accuracy of prediction. The predictive power for the green category increased significantly as the percentage of the total population classified green declined. Since approximately 88% of the model population accessed, an accuracy of 88% would have been achieved if all DEP members were classified as green. The power curve begins to flatten out as it approaches 50% classification green and rises no higher than 96.8% accurate at about 45% classification green. We decided to use the slightly smaller accuracy of 96.7% due to the significantly larger classification rate of 53.6% green.

As indicated in Figure 8, the cutoff threshold to maximize green classification accuracy was determined to be $\hat{\pi}(x) \leq .06$. A high accuracy is desired in the green classification because a misclassification might result in a DEP member not receiving needed extra recruiter attention.

GREEN CATEGORY

ACCURACY vs CLASSIFICATION SIZE

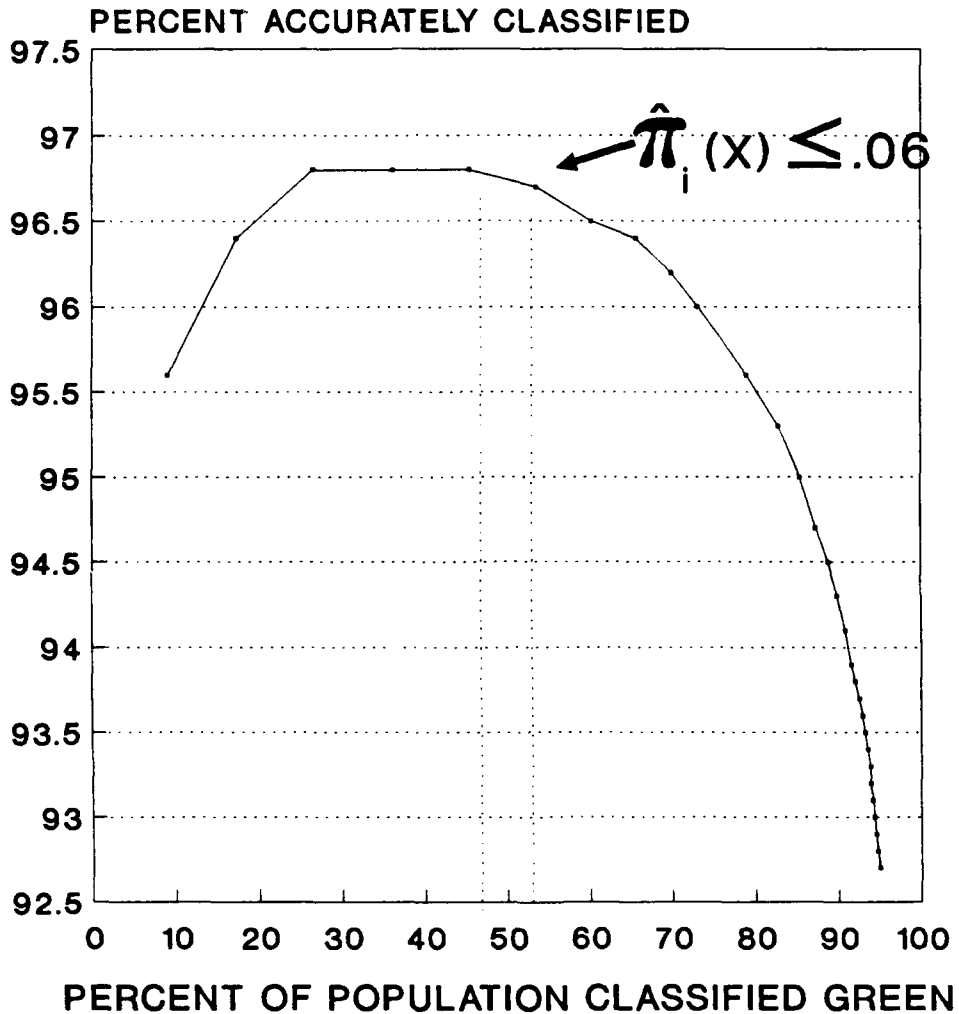


Figure 8 Model Power Green Classification

3. RED Classification

The classification of a DEP member as red by the threshold value would alert the recruiter that this individual

is a high DEP loss risk and predicted to be a DEP loss. Similar to the green classification's plotted power, Figure 9 illustrates the predictive power of the fitted model with respect to classification into the red category. As in the power of the green classification, the accuracy significantly improved as the percent of the population classified red decreased. The accuracy peaked at 89.6% with a classification of about 4% of the population as red.

Though this accuracy is not as high as that of the green classification, this still appears to be a strong prediction accuracy due to the small percentage (12%) of the population that eventually became a DEP loss. For comparative purposes, the accuracy would have been only about 12% if 100% of the population was classified red. Additionally, an error in this prediction may only result in a recruiter paying closer attention to a DEP member who may have accessed without the attention. As indicated in Figure 9, the cutoff threshold used to maximize the accuracy of those classified red was $\hat{\pi}(x) \geq .70$.

4. Final Results

As a result of the selection of these thresholds, the final model classified the data used to fit the model as depicted in Table XI. This table indicates that less than 50% (42.45%) of the population was classified as amber. As previously mentioned, the classification accuracy was strong

RED CATEGORY

ACCURACY vs CLASSIFICATION SIZE

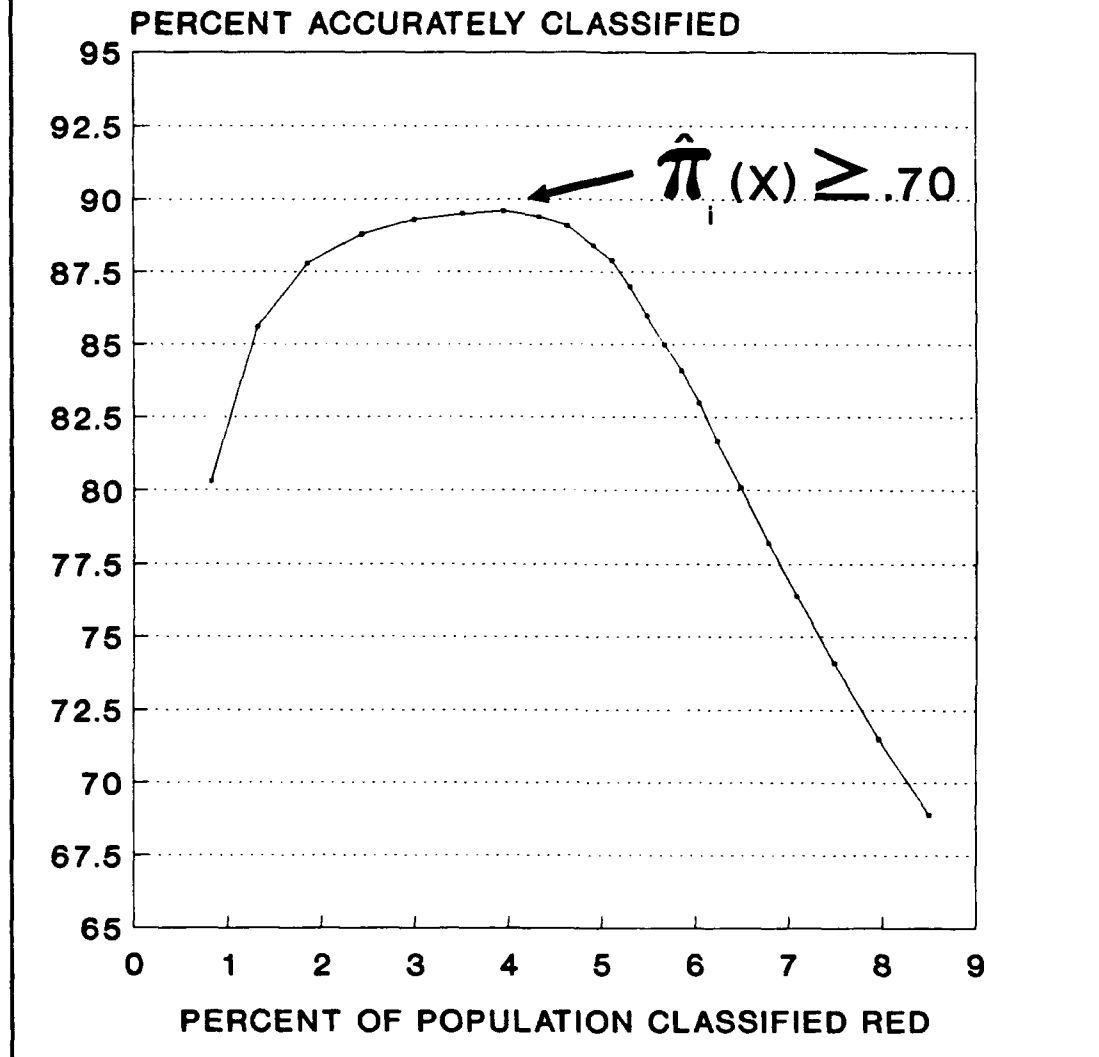


Figure 9 Model Power Red Classification

even when constrained by no more than 50% being classified as amber. The over-all classification accuracy of the threshold rule for those DEP members that eventually did access was 99.2%; it was 66.6% for those that were DEP losses.

Table XI MODEL DATA CLASSIFICATION TABLE

GROUP / CRITERIA / (PERCENT OF POPULATION)				
OBSERVED	GREEN $\pi_i(x) \leq .06$ (53.6 %)	AMBER .06 ($\pi_i(x)$) < .7 (42.45 %)	RED .7 $\leq \pi_i(x)$ (3.95 %)	PERCENT ¹ CORRECT BY Y_i
$Y_i = 0$ ACCESSION	88,544	62,141	704	99.2 %
$Y_i = 1$ DEP LOSS	3,033	10,404	6,039	66.6 %
PERCENT CORRECT BY GROUP	96.7 %		89.6 %	

NOTE: 1. The calculation for correct by Y_i does not include those classified as amber.

B. VALIDATION

The final test conducted was the validation of the fitted model on a new data set. The method of maximum likelihood ensured that the coefficients in \hat{B} were estimated so as to make the observed cases in the model data set as likely as possible. Hence, it was expected that the fitted model would perform in an optimistic manner on the model data set. Regression models with many explanatory variables at times become overly reliant on the data used to fit the model by selecting as significant, covariate patterns unique to the model data set. [Ref. 8:p. 171]

The original data set that was used to fit the model was a random 25% sample (170,685 cases) from the database of all enlistment contracts signed in FY 86 through FY 90. The new data set used for validation of the fitted model was a new

random 25% sample (171,809 cases) from the same database. Validation was conducted by calculating the logit, $g(X)$ using the estimated coefficients from the fitted model, \hat{B} in a linear combination with the covariates from the new 25% sample in equation (3). These values were then substituted into the logit transformation, equation (2), resulting in corresponding estimated probabilities, $\hat{\pi}$.

Figures 10 and 11 illustrate the predictive power of the model on a new data set as compared to the model data set. The power of the green classification on the validation data set was almost as strong as for the model data set. The maximum accuracy is obtained at the same $\hat{\pi}$ threshold with less than a .1% decrease in accuracy.

Likewise, the model performed well with the validation data set in red classification. As Figure 11 illustrates, the predictive power of the model on the validation data set was almost identical to that for the model data set. The validation data set resulted in higher prediction accuracies than the model data set when lower percentages of the validation data set were classified red.

The results of the validation effort indicate that the model is not overly reliant on the model data in either green or red classifications. Table XII summarizes the final classification results for the validation data set. Only a slightly larger percentage of individuals were classified as amber using the validation data set, still less than the

GREEN CATEGORY

ACCURACY vs CLASSIFICATION SIZE

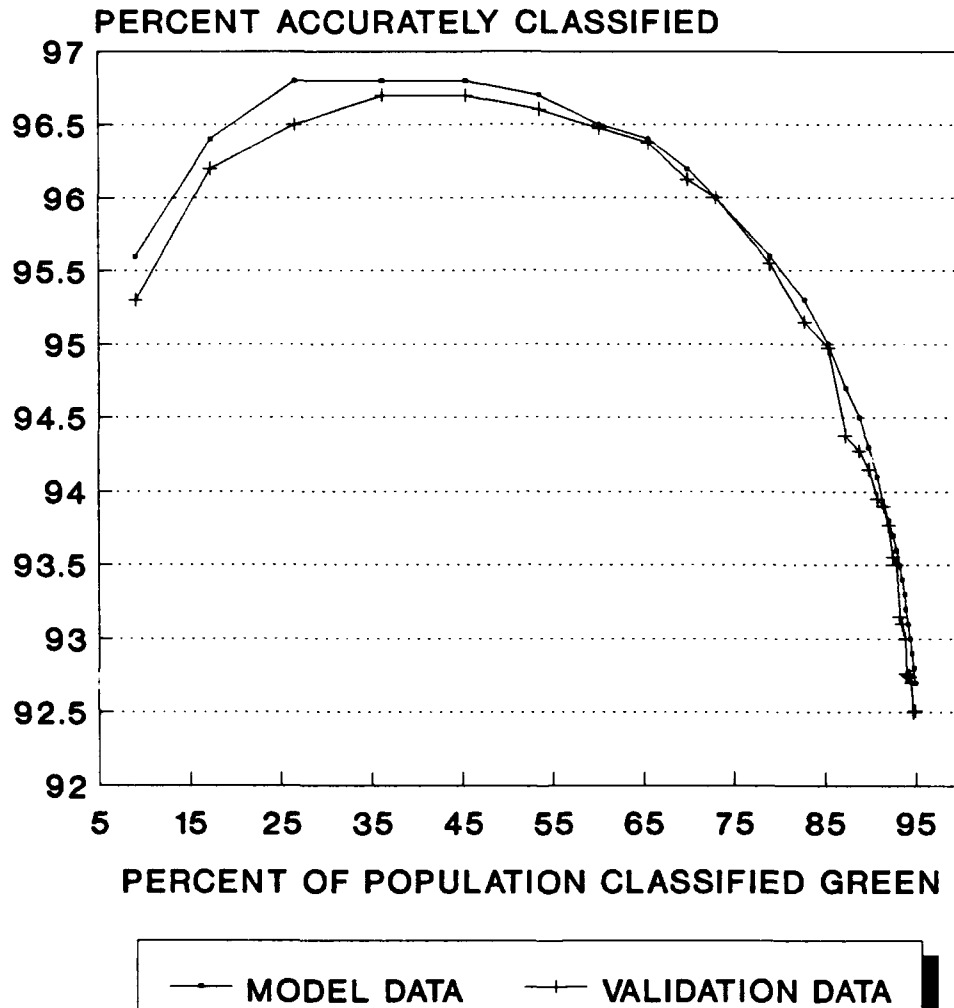


Figure 10 Green Validation Power

criterion of 50%. The red and green classification accuracies for the validation data set are only marginally smaller than the model data set. These results indicate that our model has excellent potential for predicting DEP loss outcomes for future DEP members.

RED CATEGORY

ACCURACY vs CLASSIFICATION SIZE

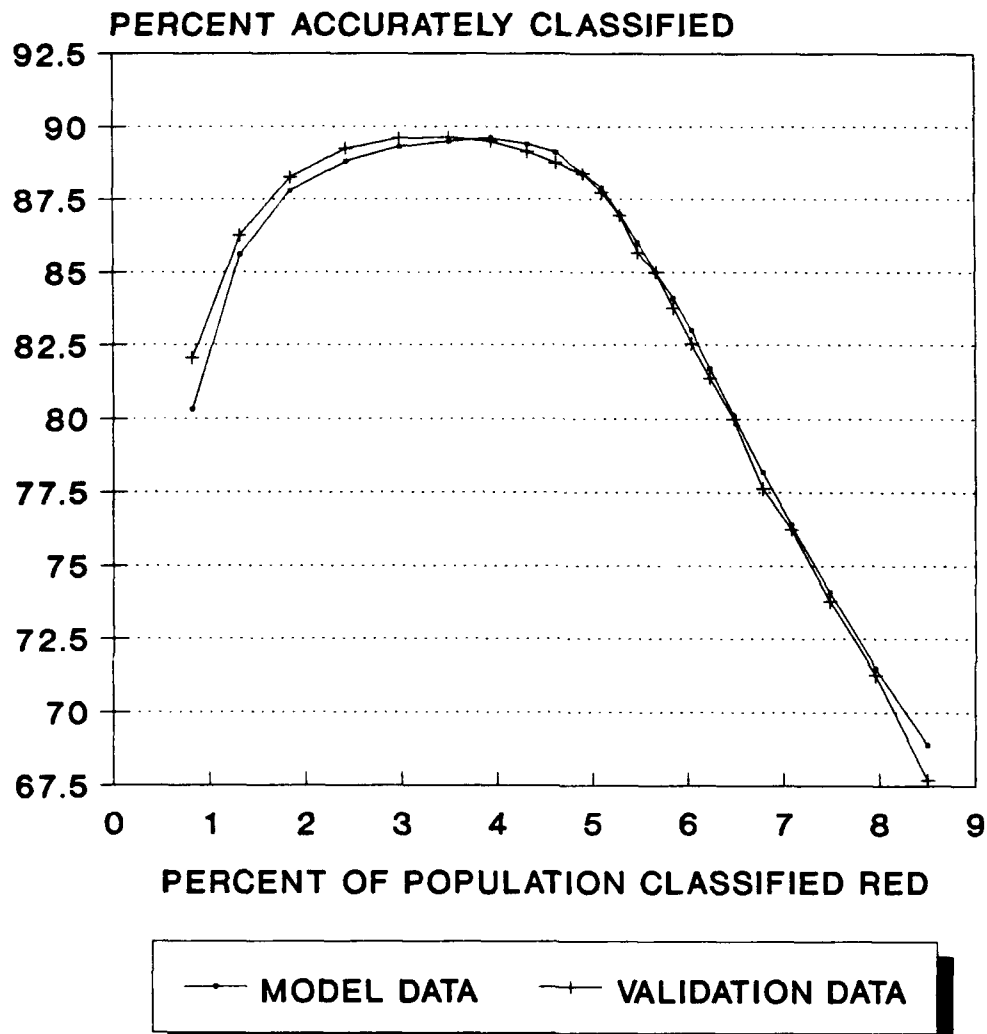


Figure 11 Red Validation Power

Table XII VALIDATION DATA CLASSIFICATION TABLE

GROUP / CRITERIA / (PERCENT OF POPULATION)				
OBSERVED	GREEN $\pi_i(x) \leq .06$ (52.9 %)	AMBER $.06 < \pi_i(x) < .7$ (43.22 %)	RED $.7 \leq \pi_i(x)$ (3.89 %)	PERCENT ¹ CORRECT BY Y_i
$Y_i = 0$ ACCESSION	87,795	63,584	698	99.2 %
$Y_i = 1$ DEP LOSS	3,070	10,667	5,995	66.13 %
PERCENT CORRECT BY GROUP	96.62 %		89.57 %	

NOTE: 1. The calculation for correct by Y_i does not include those classified as amber.

VIII. RECOMMENDATION AND CONCLUSIONS

A. RECOMMENDATIONS

Modeling human behavior is a difficult process because there are so many unknown and unmeasurable factors which ultimately affect the dependent variable being modeled. Modeling of the DEP loss process is no exception. Therefore, recommendations that follow focus on obtaining data that could possibly act as significant explanatory variables in a refined DEP loss model.

The RENO variable used in this study indicated whether the enlistment contract had been renegotiated while the recruit was in the DEP. Though obtainable through indirect means, the USAREC Minimaster database does not describe the renegotiation process beyond a binary (yes,no) variable. Whether the renegotiation was a date change, training change, or job change might be significant information.

National and local advertising have long been considered key recruiting tools by USAREC. Analysts at USAREC have been asked in the past to quantitatively demonstrate the relationships between advertising expenditures and successful recruiting operations. The NATADV and BDEADV variables used in this fitted model were aggregated to the fiscal year. These advertising variables were not for a specific media type such

as television, radio, or newspaper. More detailed, historical advertising information down to the Recruiting Battalion level by time and media type could be valuable in developing a refined DEP loss model.

USAREC uses promotion incentives such as the E-2 referral program. DEP members who refer candidates which later sign a contract are rewarded with an advanced promotion to E-2 upon entering active duty. This has proven to be a valuable recruiting tool with respect to generating contract leads. The effect that this program may have on the DEP loss process was not modeled here due to inaccessibility of the data. Inclusion of this information in the USAREC Minimaster database could significantly assist in development of an improved DEP loss model.

B. CONCLUSIONS

This modeling effort has attempted to quantify the complex DEP loss process involving many known explanatory variables. Though the model in its entirety did not fit well as measured by two statistical tests, for certain levels of estimated probability of DEP loss, $\hat{\pi}$, the model appeared to fit well. An important test of any model that might be used for predictive purposes is its validation. We demonstrated that our model performed satisfactorily on a validation data set obtained by taking a new 25% random sample from the database. With as an important of a resource management tool as the DEP,

a modeling effort that displays some success in predicting DEP loss should be pursued. We conclude that this model could prove useful in assisting recruiters in assessing DEP loss risks of individual recruits.

APPENDIX. A

Table XIII CAREER MANAGEMENT FIELD DEP LOSS ANALYSIS

<u>CLASS VARIABLE</u>	<u>VARIABLE DESCRIPTION</u>	<u>PERCENT¹ ACCESSION</u>	<u>PERCENT¹ DEP LOSS</u>
CMF	CAREER MANAGEMENT FIELD		
...00 ²	.5% CMF 00	.6	99.4
...09	.5% CMF 09	95.2	4.8
...11	13.8% CMF 11	89.4	10.6
...12	3.0% CMF 12	88.4	11.6
...13	7.5% CMF 13	90.1	9.9
...14	2.6% CMF 14	88.8	11.2
...19	4.3% CMF 19	89.7	10.3
...23	.6% CMF 23	89.8	10.2
...25	.7% CMF 25	88.7	11.3
...27	.7% CMF 27	89.0	11.0
...29	1.5% CMF 29	88.9	11.1
...31	8.7% CMF 31	88.9	11.1
...33	.5% CMF 33	89.4	10.6
...35	.6% CMF 35	88.7	11.3
...46	.1% CMF 46	86.0	14.0
...51	2.1% CMF 51	86.8	13.2
...54	.9% CMF 54	90.2	9.8
...55	.9% CMF 55	89.2	10.8
...63	10.4% CMF 63	89.1	10.9
...67	3.0% CMF 67	88.4	11.6
...71	5.7% CMF 71	86.4	13.6
...74	.4% CMF 74	84.0	16.0
...76	7.4% CMF 76	88.5	11.5
...77	1.6% CMF 77	90.0	10.0

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Table XIV CAREER MANAGEMENT FIELD DEP LOSS (CONTINUED)

<u>CLASS VARIABLE</u>	<u>VARIABLE DESCRIPTION</u>	<u>PERCENT ¹ ACCESSION</u>	<u>PERCENT ¹ DEP LOSS</u>
CMF	CAREER MANAGEMENT FIELD		
...81	.3% CMF 81	86.7	13.3
...88	3.6% CMF 88	88.3	11.7
...91	7.3% CMF 91	86.9	13.1
...93	.8% CMF 93	85.9	14.1
...94	3.1% CMF 94	88.2	11.8
...96	4.9% CMF 96	87.3	12.7
...97	.3% CMF 97	94.6	5.4
...98	1.9% CMF 98	89.2	10.8
TOTAL	TOTAL CONTRACT PERCENTAGES	88.0	12.0

NOTE: 1. Cell difference significance less than .00005 Chi-square test 2. This is not real CMF but only a surrogate "holding" CMF for a known DEP loss who is not being carried on record as a DEP loss. Discussed in Chapter IV.

Table XV RECRUITING BATTALION DEP LOSS ANALYSIS

<u>CLASS VARIABLE</u>	<u>VARIABLE DESCRIPTION</u>	<u>PERCENT ¹ ACCESSION</u>	<u>PERCENT¹ DEP LOSS</u>
BATTALION	RECRUITING BATTALION		
...1A	1.0% FROM ALBANY	85.4	14.6
...1B	2.6% FROM BALTIMORE	87.9	12.1
...1C	1.3% FROM BOSTON	83.9	16.1
...1D	1.0% FROM BRUNSWICK	87.0	13.0
...1E	1.9% FROM HARRISBURG	86.1	13.9
...1F	.9% FROM NEW HAVEN	85.9	14.1
...1G	1.9% FROM NEW YORK CITY	85.4	14.6
...1H	1.4% FROM NEWBURGH	82.8	17.2
...1K	1.6% FROM PHILADELPHIA	85.6	14.4
...1L	2.2% FROM PITTSBURGH	87.6	12.4
...1N	2.0% FROM SYRACUSE	86.9	13.1
...3A	2.5% FROM ATLANTA	88.9	11.1
...3B	1.5% FROM BECKLEY	88.4	11.6
...3C	1.5% FROM CHARLOTTE	88.6	11.4
...3D	1.9% FROM COLUMBIA	92.2	7.8
...3E	2.8% FROM JACKSONVILLE	88.9	11.1
...3F	1.7% FROM LOUISVILLE	88.6	11.4
...3G	2.5% FROM MIAMI	87.5	12.5
...3H	2.3% FROM MONTGOMERY	90.9	9.1
...3I	1.7% FROM NASHVILLE	87.1	12.9
...3J	1.7% FROM RALEIGH	91.6	8.4
...3K	1.9% FROM RICHMOND	91.3	8.7
...4A	1.5% FROM ALBUQUERQUE	89.7	10.3
...4C	2.5% FROM DALLAS	89.0	11.0
...4D	1.8% FROM DENVER	89.2	10.8
...4E	2.4% FROM HOUSTON	91.1	8.9
...4F	2.1% FROM JACKSON	89.4	10.6
...4G	2.1% FROM KANSAS CITY	88.9	11.1
...4H	2.1% FROM LITTLE ROCK	90.9	9.1
...4I	1.8% FROM NEW ORLEANS	93.8	6.2
...4J	1.6% FROM OKLAHOMA CITY	91.4	8.6
...4K	2.0% FROM SAN ANTONIO	91.9	8.1
...4N	1.9% FROM ST LOUIS	87.1	12.9

CONTINUED NEXT PAGE

Table XVI RECRUITING BATTALION DEP LOSS (CONTINUED)

<u>CLASS VARIABLE</u>	<u>VARIABLE DESCRIPTION</u>	<u>PERCENT¹ ACCESSION</u>	<u>PERCENT¹ DEP LOSS</u>
BATTALION	RECRUITING BATTALION		
...5A	2.0% FROM CHICAGO	88.1	11.9
...5B	1.4% FROM CINCINNATI	86.3	13.7
...5C	2.5% FROM CLEVELAND	86.0	14.0
...5D	1.5% FROM COLUMBUS	88.0	12.0
...5E	1.2% FROM DES MOINES	85.4	14.6
...5F	2.2% FROM DETROIT	87.4	12.6
...5H	1.8% FROM INDIANAPOLIS	86.7	13.3
...5I	2.4% FROM LANSING	86.9	13.1
...5J	1.9% FROM MILWAUKEE	85.5	14.5
...5K	1.8% FROM MINNEAPOLIS	86.3	13.7
...5L	1.7% FROM OMAHA	89.6	10.4
...5M	1.8% FROM PEORIA	87.0	13.0
...6A	1.6% FROM SAN FRANCISCO	84.6	15.4
...6E	.8% FROM HONOLULU	89.3	10.7
...6F	2.9% FROM LOS ANGELES	86.1	13.9
...6G	1.8% FROM PHOENIX	88.1	11.9
...6H	1.5% FROM PORTLAND	87.7	12.3
...6I	2.0% FROM SACRAMENTO	88.9	11.1
...6J	1.4% FROM SALT LAKE CITY	90.6	9.4
...6K	2.1% FROM SANTA ANA	87.4	12.6
...6L	2.1% FROM SEATTLE	88.5	11.5
TOTAL	ALL CONTRACTS	88.0	12.0

NOTE: 1. Cell difference significance less than .00005 Chi-square test

Table XVII ESTIMATED COEFFICIENTS EDUC, RACE, PADDMO

VARIABLE	ESTIMATED COEFFICIENT \hat{B}_i	SIGNIFICANCE LEVEL
EDUC EDUCATION STATUS AT CONTRACT		
...SENIOR	.6642	.0000
...NONGRAD	-1.4175	.0000
...DIPGRAD	1.8728	.0000
...OTHGRAD	-1.1195	.0000
RACE		
...WHITE	.2521	.0008
...OTHER	.2275	.0774
...BLACK	.0147	.8569
...ASIAN	-.3602	.1551
...HISPAN	-.1341	.0000
PADDMO PROJECTED ACCESSION MONTH		
.....JAN	.0954	.0022
.....FEB	-.1290	.0004
.....MAR	.0446	.2407
.....APR	.0012	.9777
.....MAY	.1047	.0037
.....JUN	.1116	.0029
.....JUL	.0092	.7682
.....AUG	-.0889	.0005
.....SEP	-.1781	.0000
.....OCT	.0949	.0006
.....NOV	-.0124	.6635
.....DEC	-.0532	.0000

Table XVIII ESTIMATED COEFFICIENTS FOR CMF

VARIABLE	ESTIMATED COEFFICIENT \hat{B}_i	SIGNIFICANCE LEVEL
CMF CAREER MANAGEMENT FIELD		
11	.1052	.002
31	.1243	.0009
91	.1478	.0001
63	.1130	.0018
71	.242	.0000
27	.1245	.2358
19	.0465	.3559
12	.1289	.023
96	.1324	.0025
51	.3131	.0000
94	.383	.0000
13	.1167	.0047
88	.1759	.0005
76	.0781	.0496
98	-.1797	.012
14	.0683	.2614
33	.1186	.3504
09	-2.2913	.0000
67	.0392	.503
35	-.1615	.1781
74	.3141	.0209
23	.0174	.8857
54	.0874	.392
29	.1835	.0132
97	-1.4193	.0000
93	.2513	.0069
55	.2613	.0063
25	-.002	.9827
81	-.0351	.8366
77	.2045	.0049
46	0.31	.0000

Table XIX ESTIMATED COEFFICIENTS FOR BN

VARIABLE	ESTIMATED COEFFICIENT \hat{B}_i	SIGNIFICANCE LEVEL
BN RECRUITING BATTALION		
1A	.2041	.0192
1B	1.2767	.0000
1C	.9065	.0000
1D	-.1931	.052
1E	-.3692	.0000
1F	1.1548	.0000
1G	.7244	.0000
1H	2.2415	.0000
1K	.7448	.0000
1L	-.218	.0137
1N	.2085	.0052
3A	-.0776	.2375
3B	-.606	.0000
3C	-.1493	.0672
3D	-.7523	.0000
3E	-.4442	.0000
3F	-.2836	.0045
3G	.0094	.8918
3H	-.6782	.0000
3I	-.1921	.0402
3J	-.7429	.0000
3K	-.1086	.1876
4A	-.7307	.0000
4C	.2034	.0034
4D	.0799	.3445
4E	.3142	.0001
4F	-.7908	.0000
4G	-.1932	.0069
4H	-1.2489	.0000
4I	-1.2526	.0000
4J	-.5316	.0000
4K	-.8077	.0000
4N	.0053	.9408

Table XX ESTIMATED COEFFICIENTS FOR BN (CONTINUED)

VARIABLE	ESTIMATED COEFFICIENT \hat{B}_i	SIGNIFICANCE LEVEL
BN RECRUITING BATTALION		
5A	.9058	.0000
5B	.2358	.0045
5C	.3996	.0000
5D	-.1517	.0623
5E	-.0939	.2550
5F	.8422	.0000
5H	.0722	.3109
5I	.0364	.5956
5J	.1939	.0074
5K	.3535	.0000
5L	-.9025	.0000
5M	.5068	.0000
6A	1.0243	.0000
6E	-.5372	.0000
6F	.2149	.0026
6G	-.0333	.6434
6H	-.2194	.0112
6I	-.4852	.0000
6J	-.5277	.0000
6K	.3903	.0000
6L	.080	.0000

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4. Defense Technical Information Center 2
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5. U.S. Army Library 1
Army Study Documentation and Information Retrieval System
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